Journal of Transport Geography 64 (2017) 65–76

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Is traffic congestion overrated? Examining the highly variable effects of congestion on travel and accessibility

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ARTICLE INFO

Keywords:
Accessibility
Congestion
Travel behavior

ABSTRACT

Congestion is universally unpopular, but is it always a problem? Are some places more "congestion-adapted" than others? Using data for Los Angeles, we examine whether the geographies of congestion and accessibility are distinct by mapping and describing them across neighborhoods. We then estimate a series of regression models of trip-making to test the net effects of traffic delays on behavior. We find that there are places where people make many trips and engage in many activities despite lots of congestion, which tend to be more central, built-up areas that host many short trips; in other places, high congestion and low activity coincide. Why the variance? While congestion can constrain mobility and reduce accessibility, traffic is also associated with agglomerations of activity and is thus a byproduct of proximity-based accessibility. Whether agglomeration and congestion have net positive or negative impacts on activity participation thus varies substantially over space. Controlling for factors such as income and working at home, we find that the effects of congestion on access depend on whether congestion-adaptive travel choices (such as walking and making shorter trips to nearby destinations) are viable. Because "congestion-adapted" places tend to host more trip-making, planners may be justified in creating more such places in order to increase accessibility, even if doing so makes absolute levels of congestion worse in the process.

1. Introduction

Traffic congestion is widely perceived as among the most vexing of urban ills – one that exacts high social, economic, and environmental costs on residents and firms alike. But is congestion really all it's cracked down to be? Perhaps not.

Many urban and transportation planners assume that better land use and transportation integration will reduce congestion by promoting both compact development and alternatives to private vehicle travel. These efforts to increase walk- and transit-friendly environments include increasing development densities, mixing land uses, and devoting more street space to support other than motor vehicle movements (Bogert et al., 2011; Ewing, 2008; Talen and Koschinsky, 2013; US Environmental Protection Agency, 2016). But while such urbanizing policies may increase travel choices, they typically *increase* traffic delays as well, and in many communities have occasioned visceral pushback from residents and the officials they elect over rising congestion levels (Downs, 2005; Obrinsky and Stein, 2007). But if these policies are successful at increasing the number and variety of nearby destinations accessible by foot, bike, bus, and car, trip-making and utility may well increase in spite of worsening congestion.

To examine this issue, we assess the accessibility/congestion relationship using data for Los Angeles, one of the largest and most congested U.S. metropolitan areas. We find that some neighborhoods are more "congestion-adapted" than others by facilitating high levels of personal and economic activity across shorter distances and via non-auto modes, often in spite of high levels of congestion. In contrast, accessibility in other, less congestion-adapted areas may be strongly inversely related to congestion levels, which square with both intuition and the traditional tenets of transportation engineering practice. So while bumper-to-bumper traffic may be similarly frustrating to drivers everywhere, its social and economic effects likely vary substantially from place to place.

While the concept of accessibility has gained considerable traction among urban and transportation scholars as a more meaningful measure of how transportation systems enable social and economic activity, such measures are only beginning to trickle into professional transportation engineering and planning practice. This article examines how measures of accessibility may produce very different results than measures of delay. The common use of congestion measures that

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http://dx.doi.org/10.1016/j.jtrangeo.2017.08.007
Received 25 October 2016; Received in revised form 24 June 2017; Accepted 20 August 2017

privilege speed over accessibility may lead to policy and planning outcomes (such as discouraging further development in built-up, congested areas) that inadvertently reduce rather than increase access. When and under what circumstances worsening traffic congestion should be viewed as irritating but relatively benign versus serious and costly is a pressing question for planners seeking to improve accessibility amidst skeptical residents and elected officials worried about traffic.

2. Thinking about accessibility and congestion

Traffic congestion has grown, albeit unevenly over the past half-century. According to the Texas Transportation Institute (TTI), the absolute levels of traffic delays and their rates of growth are highest in the largest metropolitan areas, but comparatively modest in smaller metros. The TTI also estimates the costs of congestion delays (relative to free-flow speeds) at $160 billion in wasted time and fuel across U.S. urban areas in 2015 (Schrank et al., 2015). Though certainly aggravating for drivers and passengers, congestion levels are not a direct measure of access, whether to jobs, shopping or other activities. As such, widely cited measures of the economic costs of congestion are problematic.

Nearly all congestion measures reflect aggregate traffic flows and potential mobility, but do not take into account other factors that determine accessibility, such as destination proximity or individual and household circumstances. As such, the emergent consensus among transportation planning researchers – that access matters more to travelers than mobility – is likely undermined by a continued emphasis on traffic congestion among public officials, and congestion metrics commonly used by traffic engineers and planners (Handy, 2002; Levine and Garb, 2002; Wachs and Kumagai, 1973).

Still, we expect that traffic congestion does play a role in accessibility. Slow speeds increase the amount of time needed to reach an activity, yet places of concentrated activity will generate the traffic that leads to slowdowns. Thus, we observe the worst traffic congestion in some of the most economically and socially vibrant places in the nation, from Manhattan to downtown San Francisco. Agglomeration theory suggests that activities cluster, whether in cities, districts, or even a single street, because of benefits to productivity fostered by such concentration (Anas et al., 1998; Fujita and Thisse, 1996; Glaeser and Kahn, 2004; Vernon, 1972). However, along with the benefits arise costs, most notably in the form of congestion delays. Furthermore, congestion is an experienced phenomenon, and human perceptions and responses to traffic will depend on a host of factors including trip purposes, timing, and habits (Salomon and Mokhtarian, 1997; Wener et al., 2005). Thus, traffic congestion and accessibility are not likely to have a simple relationship, such as where more delay always results in reduced access.

Empirically, accessibility measurement is different from measuring traffic congestion in two ways. First, access is usually measured in terms of individuals, households, firms, or places, while congestion is measured in terms of features of the transportation network, such as vehicles, roads, or the system as a whole. Second, access is conceptually broad and a wide range of measures can be applied depending on a particular conceptualization (Levinson and Krizek, 2005). Traffic congestion, though, tends to emphasize a consistent set of established metrics, typically capturing either the velocity or volume of vehicles on roadways or the network as a whole (Papacostas and Prevedouros, 2000). Volume and speed metrics make the road network the object of analysis, rather than as simply a means to other ends. Ultimately, the definitional and empirical contradictions between accessibility and congestion result in two largely incompatible approaches to evaluating transportation system functionality (Levine and Garb, 2002).

2.1. Conceptualizing accessibility

Accessibility can be understood in terms of individuals, households, or firms, or it can apply to society broadly. Hansen (1959) introduced accessibility as a phenomenon of travel and land use, underscoring that transportation systems provide opportunities for interaction. Kevin Lynch (1981) assigned social implications to accessibility such as diversity, equity, and self-determination. Potential variations in access among groups or places can guide decision-makers seeking to identify beneficiaries and possible losers from a proposed project, information that congestion or mobility metrics cannot directly transmit.

Because of its conceptual nature, perspectives on accessibility hinge on how it is defined and measured. For example, changes to access, such as by increasing densities, have been posited as a potential approach to reducing vehicle miles traveled (Handy, 2002). However, empirical findings have not consistently borne this supposition out (Ewing and Cervero, 2010) because, among other things, observable changes in population or activity density usually occur at the scale of an individual development or, at most, district. But decisions about vehicle ownership and use are based both on individual characteristics as well as the larger spatial context within which people travel. The population density of these larger spatial contexts, such as a city or region, change very slowly even if some districts within them change substantially.

Researchers have taken diverse approaches to measuring accessibility (Levinson and Krizek, 2005). One key difference is that measures may operate at the level of individuals/households or at the level of places (Kwan et al., 2003). Place-based accessibility measures, including gravity and cumulative opportunity metrics, capture the distribution of activities or opportunities around a location, primarily accounting for the impedances between the location and the set of activity destinations (Handy and Niemeier, 1997; Hansen, 1959). Impedances often are characterized in terms of travel times over a transportation network, and thus may be applied to specific modes, such as driving or public transit (Handy, 2002).

Person-based accessibility is a function of space and time impedances, as well as the individual and household characteristics of travelers. Income, for example, is a significant modifier of accessibility, shaping both activity and travel options (Redmond and Mokhtarian, 2001). Additionally, immigration status, gender, age, race and ethnicity, and other factors can modify accessibility (Kwan and Weber, 2003). Thus, access will vary from person to person at a single location, even when holding impedances to a set of opportunities along a network constant. For example, El-Geneidy and Levinson (2006) present a model of person-based access, where utility is determined by the set of choices applicable to a given individual, recognizing variations in the value of access across individuals.

2.2. Bridging congestion and accessibility

Surprisingly little research explores the relationship between congestion and accessibility. Extant research generally frames congestion as a drag on accessibility. Salomon and Mokhtarian (1997) proposed a framework for understanding human responses to congestion as "coping;" they offer numerous behavioral responses to congestion including shifting destinations, time of travel, and mode choice, underscoring that the effects of congestion on individuals' accessibility are likely modified by a wide range of factors from nearby destinations to job flexibility to available modes of travel.

Building on this behavioral approach, Weber and Kwan (2002) find that congestion's diurnal variability significantly affects accessibility from hour to hour as well, with a negative relationship between times of congestion and access. In the case of firms, Sweet (2014) finds that while regional congestion may be a diseconomy to firms, localized congestion may act as a proxy for amenities valued by a wide range of firms. Hou (2016) confirms that local and regional congestion have differential effects on firm location, depending on sector, with office-

based firms more negatively affected by regional congestion, while production-related businesses are more negatively affected by local congestion. In terms of policy, links between congestion, mobility, and accessibility are central to the equity of congestion pricing. For example, Levine and Garb (2002) argue that congestion pricing can *lower* the cost of access if the revenues are used to invest in alternatives to driving. Finally, Thomas et al. (2016) find that in Los Angeles, accessibility to jobs in most neighborhoods is far more dependent on proximity than road speeds, suggesting a relatively weak relationship overall between congestion and accessibility.

2.3. Conceptualizing congestion's effects on accessibility

We propose a framework for understanding congestion's effects on accessibility. Of three pathways by which congestion influences access, first, and most obviously, congestion will reduce speeds, increasing impedances and thus reducing accessibility. Second, inasmuch as congestion is a result of agglomerations of activities, it will be associated with increased accessibility, even if it to some extent attenuates the benefits of agglomeration. Third, congestion is an experienced phenomenon, and it will affect choices about where to live, work, and play. Experiential effects may operate over the long run, thereby shifting the choice set and activity/travel choices in ways that do not reflect short-run costs and benefits. Together these factors suggest a complex, multifaceted relationship between congestion and accessibility. In particular, impedance, agglomerative effects, and individual, experiential factors will vary among both places and individuals.

We expect that an area will exhibit high levels of accessibility, even with congested roads if activities are proximate, while high speeds on roadways may result in low accessibility if activities are highly dispersed. Historically, transportation policies aimed at reducing congestion attempted to enhance mobility by increasing capacity. Some advocates of accessibility claim that enhanced mobility in urban areas has a perverse effect because it induces land uses to disperse, with resultant increases in travel times and costs (Grengs et al., 2010; Levine and Garb, 2002). Conversely, some proposed approaches to increasing accessibility may increase road congestion, such as increasing densities, or slowing streets and increasing the cost of parking to improve non-motorized forms of accessibility, such as biking and walking (Levine et al., 2007).

Traffic congestion certainly has negative impacts, but it is also a byproduct of economic activity and social interaction (Taylor, 2004; Wachs and Kumagai, 1973; Sweet, 2014). From a regional economic point of view, congestion can be understood as inhibiting the potential for growth. However, whether reducing congestion actually increases activity is likely to be determined by how cities address their congestion woes. Congestion pricing and even capacity enhancements can reduce delays and increase the potential for activity as well. Providing alternatives to driving, whether via other travel modes or through information technologies, may be just as effective as facilitating access to destinations. On the other hand, an economic recession, odd/even license plate driving prohibitions, or other vehicle travel reduction policies may well reduce congestion, but in the process increase overall access costs – if such phenomena or policies fail to offer travelers meaningful alternative transportation choices in the process.

Though traffic congestion may slow economic growth or activity, can we observe this effect locally, rather than regionally? In a provocative paper, Glaeser and Kahn (2004) suggest that Los Angeles' regional growth may have begun to suffer because the costs of traffic congestion had started to outweigh agglomeration benefits. Still, this paper does not look at local effects, though congestion and activity both vary substantially across Los Angeles or any urban region.

Finally, an alternative cognitive framework for accessibility depends on perceptions (Kwan, 1998; Weber and Kwan, 2002). An individual's experience with traffic affects her/his sense of accessible destinations, even congestion may not be as intense as perceived (Wener et al., 2005). In fact, psychologists have found perceptions of congestion to be tied as much to individual characteristics as to conditions on the road (Hennessy et al., 2000). Building on this complex set of considerations, we ask whether both local and individual factors may lead to varying responses to congestion. Specifically, how (if at all) are activity patterns, as an empirical measure of access, influenced by traffic delays?

3. Data and methodology

Given its notorious reputation for chronic traffic congestion, we selected metropolitan Los Angeles as an ideal laboratory for analyzing how traffic delays affect both access to opportunities and travel behavior. In addition to its consistently high congestion ranking in the TTI Urban Mobility Report, much of the Los Angeles-Orange County region is surprisingly dense, nearly 7000 persons per square mile, and in fact is the densest urbanized area in the United States (US Census Bureau, 2012). However, this average density encompasses a range of neighborhood forms, from old walkable neighborhoods built around former streetcar stops, to gated-communities on the periphery of National Forests.

We combined data from two sources to conduct our analysis: (1) the Southern California Association of Governments (SCAG) Travel and Congestion Survey and (2) SCAG estimates of traffic volumes and delays for both arterial streets and freeways. We first use a geographic information system (GIS) to analyze the spatial relationships between accessibility and traffic congestion at regional and sub-regional scales. To investigate how activity participation varies across space and individuals in the face of congestion, we then estimate multi-variate regression models of trips.

3.1. Data sources

SCAG is the metropolitan planning organization for Los Angeles and the rest of Southern California outside of San Diego, and in that role produces a Regional Transportation Plan, or RTP. In preparing the RTP, SCAG develops regional travel demand models drawing on collected household travel and transportation network data in order to estimate current and forecast future travel patterns and congestion delays (Meyer Mohaddes Associates Inc., 2004). Personal travel data for these models are drawn from occasionally updated regional household travel surveys that gather detailed household and travel information across small units of geography. The level of spatial detail in regional household travel surveys offer analysts considerably more information than is available from regularly updated national data sources like the U.S. Census or the National Household Travel Survey. As this research commenced, the most recent household travel survey data for metropolitan Los Angeles were collected in 2002 for the 2003–2004 RTP (the SCAG household travel survey was recently updated, but the data were not available in time for us to use in the analysis). Because we are not examining how the effects of congestion might be changing over time, and are instead examining the variable effects of traffic delays on travel behavior across neighborhoods and districts in Southern California, the data available to us suit our purposes. Our next phase of this research, however, may examine whether the relationships among congestion, accessibility, and household travel may be changing over time.

The SCAG survey gathers extensive detail on activity patterns and associated travel for each person in each of the 15,000 households queried. The household socio-economic data include traveler's age, sex, race/ethnicity, and employment status, as well as household size, income, and auto availability. Data for each trip made by each household member include timing, duration, origins, destinations, links, purpose, travel mode, cost, and so on (NuStats, 2003). The entire SCAG region, which includes much of the Mojave and U.S. portion of the Colorado Deserts, is larger than New England and enormously complex, spanning over 98,400 km^2. Most residents, however, live in or near the Los

Angeles Basin, which is the most densely developed and congested portion of the region. Accordingly, we limited the data analyzed to the 5830 surveyed households in the coastal plains and foothills of the LA Basin in Los Angeles and Orange Counties. We also narrowed our data to include only households where the primary respondent was over 17 and under 66 years of age and employed in order to control for life-cycle-based differences activity and trip-making among children and older adults.

In addition to the SCAG household travel survey data, we also include in this analysis SCAG Regional Screenline Traffic Count data for 2003, which includes estimated traffic volumes and delays on all major arterials and freeways across the SCAG region. These traffic flows are estimated separately for the morning weekday peak period, midday, the afternoon/evening weekday peaks, evenings, and weekends; they are based on automated traffic counts and extrapolated to estimate traffic levels for all road segments across the five time periods described above (Meyer Mohaddes Associates Inc., 2004). These traffic estimates include data on road link capacity and traffic volumes in both directions of travel, and include volume-to-capacity (V/C) ratios as well.

3.2. Operationalizing the variables of interest

We employ a relatively novel, albeit straightforward method for defining and measuring localized congestion. We begin with a widely used measure of traffic on road networks, the volume-to-capacity (V/C) ratio (Papacostas and Prevedouros, 2000). The SCAG Regional Traffic Screenline Study data include V/C ratios for all freeways and arterial road segments in our study area. For each of the > 40,000 road segments in the dataset we calculated the maximum V/C value in either travel direction in either (AM or PM) peak period; we designated that value as our congestion measure of interest. The estimated V/C values in the SCAG data range from zero (indicating no traffic volume at all) to greater than one (indicating the forecast demand on a given segment exceeds capacity). Because the V/C ratios analyzed here are calibrated, estimated, and validated as part of the regional travel forecasting process, the ratios are perhaps best characterized conceptually as demand/capacity (D/C) ratios in that these ratios can exceed one even as observed flows break down, and even decline, as traffic volumes reach road capacity, resulting in what some describe as hyper-congestion. Thus these modeled V/C ratios function effectively for our purpose of measuring the generalized intensity of congestion.

Using peak V/C measures along the network, we interpolate a "surface" of localized congestion based on nearby link congestion levels weighted by both road capacity and distance. The technique we use to create the variable congestion surface for our analysis is the kriging method of surface interpolation. Kriging is one of a family of methods used in geographic information systems to estimate a grid of values from available known values distributed asymmetrically in space (Miller, 2004). In kriging these data, we both accounted for regional patterns of variation in the data and, in addition, tested for the normal distribution of input values (Davis, 1986). While we examine the distribution of congestion values across a Euclidean surface of places (e.g. neighborhoods), the assignment of traffic and congestion using kriging has also been applied to a regional road network-weighted surface (Wang and Kockelman, 2009; Wang, 2013).

The results of our data preparation described above are presented in Fig. 1, which shows the distinct, variable levels of peak congestion across our study area, with largest cluster of traffic delays running in a 25 km arc between Santa Monica in the west to Downtown Los Angeles in the east. This most congested part of the region is large (250 km^2) and relatively densely developed (5200 persons per $kilometer^2$), with major clusters of employment in Downtown LA, Silver Lake/Hollywood, West Hollywood/Beverly Hills, Culver City, UCLA/Westwood, and Santa Monica. Known for its many heavily trafficked freeways, the distribution of chronic freeway congestion generally tracks the patterns of arterial traffic delays; some exceptions to this pattern include the truck-heavy Long Beach Freeway (I-710), which connects the Ports of Long Beach and Los Angeles with the rail yards southeast of Downtown Los Angeles.

With respect to the concept of accessibility, we ascribe to it both spatial and socio-demographic components, consistent with the literature reviewed above. Because congestion is both an explicitly spatial and temporal phenomenon, our goal is to examine its effects in term of its influence on human activity patterns. These activity patterns are evidence of both the utility of a range of opportunities, or choice set, available to individuals, as well as the potential social costs of those choices (El-Geneidy and Levinson, 2006). The SCAG household activity survey data present many options for quantifying individual accessibility, including the number of activities in which each individual engages, the characteristics of each of those activities, the part of the region within which the activities occur, the means by which individuals travel to each activity, and (when the survey data are combined with land use and/or census data) the number and type of opportunities available to travelers within given activity spaces. For this study we measure activity participation in terms of the number of activities participated in by a respondent, controlling for localized congestion, the distance traveled to each of those activities, mode of travel, and a range of socio-demographic variables.

We operationalize individual accessibility in terms of all types of activity-oriented trips – in other words, any trip with a reported purpose whether utilitarian or recreational, regardless of travel mode or trip length. All trip purposes are assigned equal value so that accessibility is measured terms of the number of activities in which a respondent engages, where, ceteris paribus, more activity engagement implies increased accessibility. Each activity-accessing trip counts as a separate access-producing trip, regardless of whether the trip is standalone or part of a chain of trips. While there is not likely to be a precise, linear relationship between the number of activities in which one engages and individual utility derived from those activities – and, in fact, there may be a disutility associated with excessive activity engagement or with particular activities – the significant correlation between trip-making and activity spaces observed in previous studies (Schönfelder and Axhausen, 2003) suggests a relationship between trip-making and access to opportunities. To account for the potential social costs of depending largely or exclusively on automobility as a means for access, we account for both distance traveled and travel mode in our analysis as well. The relationships among activity participation, trip time, trip distance, and mode are causally complex and likely jointly determined at the level of individuals and households (Salomon and Mokhtarian, 1997; Van Wee et al., 2006). For this investigation, however, we emphasize a single outcome of interest – activity participation – and we ask how associations between activity participation and the other factors vary across built environment contexts in the Los Angeles region. This allows us, for example, to compare activity participation between densely developed, congested areas and sparsely developed areas with little congestion, controlling for an array of factors.

The median number of trips per day (including journeys to and from work) in our sample is four, and Fig. 2 displays spatial variation in these daily trip rates across our study area. Low average rates of trip-making are seen in the central core of the region (between downtown Long Beach in the south to downtown Los Angeles in the north), which is home to large numbers of low-income and minority households. Conversely, higher-than-median rates of trip-making are common in more outlying, affluent parts of the region, though with notable pockets of variation. In fact, spatial patterns of trip-making shown in Fig. 2 generally align with spatial patterns of household income, as shown in Table 1 below. This coincidence of trip-making rates and household income is consistent with the literature, which has found a strong, positive relationship between the two (Redmond and Mokhtarian, 2001).

An Appendix A documents Moran's I tests of significant clustering or dispersion of the dependent and independent variables, as well as

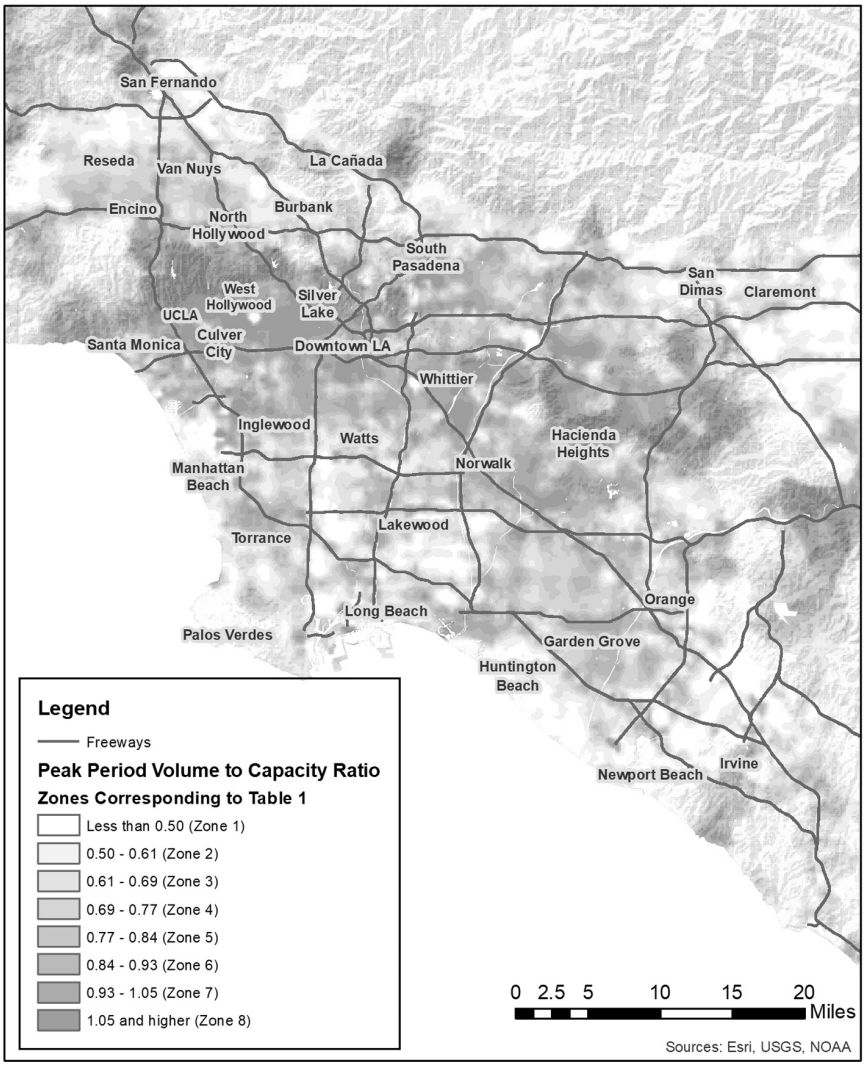

Fig. 1. Generalized traffic congestion in the Los Angeles region.

residuals for the models presented later in the paper. A finding of significance at the threshold of $p < 0.05$ suggests that variable values are distributed non-randomly across the region. We observe that several of the variables do exhibit a significant level of spatial clustering, as we would expect. For example, the significant clustering of congestion is observable in Fig. 1, and clustering of household income, household structure (age and number of students), language, race, education, and activity density are consistent with our understanding of a large, relatively racially- and class-segregated urban region like Los Angeles.

In addition to measuring and mapping traffic congestion and household activity patterns in space, we operationalize local built environment spatial accessibility via a measure of activity density. As noted above, the relative dearth or abundance of potential activities (e.g. grocery stores, nightclubs, and auto mechanics) near a given residence importantly affects the relationship among individual travel choices, activity outcomes, and nearby congestion levels. We estimate the density of trip ends – destinations – across the region (Fig. 3). In order to measure the variety and density of local destination opportunities, we calculated the survey-weighted density of destinations for each traveler's home traffic analysis zone (TAZ) using SCAG household travel survey data on the number of destinations accessed by survey respondents in each TAZ.

3.3. Analytic methodologies

Above we describe our measures of travel behavior, local congestion, and activity density, and propose a conceptual relationship among them. Below we examine this relationship. Section 4.1 explores the relationships among our variables of interest through a descriptive data analysis and an exploratory spatial analysis, presenting trip-making patterns as they vary across groups and neighborhoods defined by local congestion. While the analysis is descriptive rather than inferential, statistical comparisons of mean travel behavior across groups defined by local congestion, using *t*-tests of means at the 95% confidence level, are reported in Table 1.

Section 4.2 reports on multivariate statistical modeling to examine three key trip-making characteristics – number of trips, likelihood of driving, and likelihood of walking – and how congestion and other factors are associated these outcomes across individuals grouped by residential location activity density. We tested an array of model forms in conducting this analysis, but present only the best performing models here. Daily trips are modeled using negative binomial regression, and likelihood of driving and walking are modeled with logistic regression. Negative binomial regression is a type of multivariate analysis that models counts such as the number of trips taken in the day. It is similar to Poisson regression but better addresses the relatively high levels of dispersion in the number of trips each survey respondent takes relative

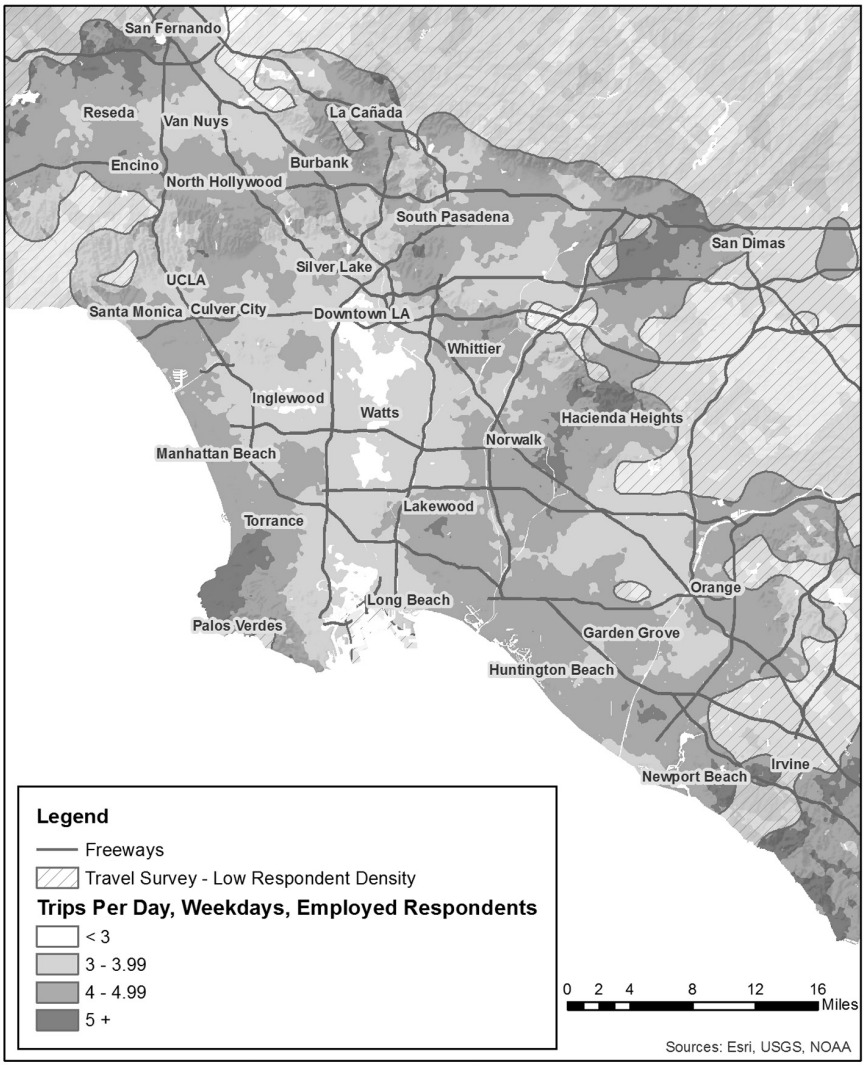

Fig. 2. Distribution of household trips in the LA region.

to the mean number of trips per day. Other researchers (Kawamoto, 2003; Kwan et al., 2003; Schönfelder and Axhausen, 2003) have constructed similar models to understand trip-making patterns. The models use survey weights supplied with the SCAG travel survey. We use a standard 95% confidence level ($p < 0.05$) for the determination of coefficient significance, and reviewed models for overall significance using Wald's chi-square.

The presented models account for non-spatial characteristics of the data, such as using a negative binomial to model overdispersed count data and weighting observations by supplied survey weights. However, the models do not include spatial terms or directly account for spatial dependence by method, such as with geographically-weighted regression – which we also tested but do not present here. Global models that include spatially dependent terms can still be appropriate and well-specified if the residuals of those models are distributed randomly across space (Anselin, 2008). Therefore, we tested our models for the spatial distribution of their deviance residuals using Moran's I, following Lin and Zhang (2007). “Deviance residuals,” described in McCullagh and Nelder (1989) as appropriate for goodness-of-fit tests in generalized linear models including of the type used in the paper, are used by Lin and Zhang (2007) to diagnose spatial autocorrelation in model residuals. These results are presented in Appendix A.

4. Analysis and findings

4.1. Congestion and trip-making

Places where less vehicle travel is required to access an equivalent set of opportunities should be of great interest to planners concerned with auto dependence, vehicle emissions, traffic congestion, and accessibility. Table 1 shows how the characteristics of survey respondents' weekday trips – number, mode, and distance – vary by congestion levels. The table shows variation in person travel for individuals residing within eight zones defined by the localized congestion measure illustrated in Fig. 1. People living in Zone 1 experience, on average, the least congestion around their homes; those in Zone 8 experience the highest. In addition to differences in trip-making, the average density of activity destinations per square kilometer within each zone, as reported in the survey, is also included. The table includes average values for those in each zone, accounting for the person-weights supplied with the survey. Variation in travel across congestion levels is shown first for all respondents, and then below for those in the top three income categories in the survey (> $75,000 yearly household income), in order to illustrate the role of socio-economic status in the congestion-accessibility relationship.

Examining respondents at all income levels, some clear linear relationships are evident. While the total number of trips taken in a day

Table 1
Trip-making and destination densities by congestion levels.[1,2]

Congestion zone	V/C ratio range		Average daily trips by mode				Daily distance travelled[3] (km)	Activity dens.[4] (km^2)
	Min	Max	All modes	Driving	Walking	Transit		
All income levels								
1 – lowest	Less than	0.50	5.32^{A}	4.68^{A}	0.22^{A}	0.04^{A}	40,467^{A}	8,236^{A}
2	0.50	0.61	5.23^{A,B}	4.61^{A,B}	0.27^{A}	0.04^{A}	36,950^{A}	11,439^{B}
3	0.61	0.69	5.09^{A,B}	4.45^{A,B}	0.21^{A}	0.03^{A}	33,658^{A,B}	11,278^{B}
4	0.69	0.77	5.01^{A,B}	4.26^{A,B}	0.30^{A,B}	0.12^{A,B}	37,356^{A}	12,044^{B,C}
5	0.77	0.84	4.89^{A,B}	4.17^{B}	0.24^{A}	0.08^{A}	49,243^{A,B}	14,243^{D,E}
6	0.84	0.93	5.15^{A,B}	4.45^{A,B}	0.32^{A,B}	0.04^{A}	33,945^{A,B}	13,072^{C,D}
7	0.93	1.05	5.09^{A,B}	4.22^{A,B,C}	0.39^{A,B}	0.09^{A,B}	31,289^{A,B}	15,448^{E}
8 – highest	1.05	or higher	4.85^{B}	3.69^{C}	0.48^{B}	0.23^{B}	29,104^{B}	19,958^{F}
Yearly household income > $75,000								
1 – lowest	Less than	0.50	5.27	4.54	0.24	0.08	44,412	6,452^{A}
2	0.50	0.61	5.56	5.10	0.21	0.00	45,678	8,950^{B}
3	0.61	0.69	5.27	4.79	0.12	0.00	40,693	9,957^{B,C}
4	0.69	0.77	5.37	4.90	0.16	0.01	41,870	10,592^{B,C,D}
5	0.77	0.84	5.47	4.91	0.21	0.00	36,765	13,759^{D,E}
6	0.84	0.93	5.05	4.62	0.13	0.00	34,479	10,650^{C,D}
7	0.93	1.05	5.34	4.88	0.22	0.00	35,870	13,775^{E}
8 – highest	1.05	or higher	4.89	4.47	0.11	0.00	35,345	12,795^{D,E}

[1] Average characteristics for individuals residing within congestion zone.
[2] Statistically significant differences between mean values for each congestion zone are denoted with superscripted letters. The letters can be interpreted as follows: if two values share a letter, they are *not* significantly different statistically at the 95% confidence level, estimated with pairwise *t*-tests of mean differences. Note that for columns with no statistically significant differences, letters are not shown.
[3] Average sum of estimated trip distances for individuals in the zone on weekdays, reported in travel survey.
[4] Average density of destinations reported in travel survey in transportation analysis zone containing respondent household.

varies only slightly relative to congestion, travel mode across all incomes varies substantially, with increased driving and reduced walking and transit use evident in higher income households. In addition, individual daily distance traveled – by any mode – declines markedly as congestion rises. Finally, congestion and activity density have a very strong direct relationship, with the least congested places having less than half the number of destinations per square kilometer as the most congested places.

For households that make at least $75,000 in yearly income, travel mode has little relationship to congestion, with driving, walking, and transit rates showing no clear trends. Here too there is an inverse relationship between daily distance traveled and activity density, though this inverse relationship is less pronounced than for the sample as a whole. Overall, these descriptive statistics show only a weak inverse relationship between congestion and *quantity* of trips, but a much stronger relationship between congestion and *how* individuals travel, with lower trip distances and more travel by modes other than driving in the most congested areas. Finally, and importantly for this study, activity density (a measure of local accessibility not accounting for speeds) is strongly positively correlated with congestion, as expected.

Table 2 reframes the relationships introduced in Table 1 to explore local variation in congestion and activity density across two key variables of concern – number of daily trips and median trip distances. We estimate median trip lengths for each survey respondent from all trips of any mode, and include "trips" of no length (home-based activities). By organizing local travel behavior in terms of both trip length and count, we observe possible accessibility "sweet spots," where individuals make many trips but over relatively short distances, as well as locales with the opposite behavior – fewer, long trips. If higher levels of trip-making reflect higher levels of individual accessibility and activity participation, but longer distance trips – all else equal – reflect higher personal and social costs to complete a given trip, then an ideal locale would be one where individuals make many, short trips.

Such activity sweet spots exist, even in Los Angeles. Other than in the urban core where trip-making, regardless of trip distance, is low, places where individuals tend to make both more than average and shorter than average trips are located throughout the region (shown in darker gray in Fig. 4). In these places, trip-making is higher than the median (4 trips) for survey respondents and average trip lengths are below the median (approximately 6 km); thus accessibility is less tightly linked to mobility. Some of these locations, such as Santa Monica, West Hollywood, and Newport Beach, are among the most well-known and popular areas in Los Angeles. Other locations, however, like Reseda, Whittier, and Garden Grove, are lower-income ethnic enclaves. Conversely, the areas where individuals make fewer, longer trips – an undesirable situation for both individuals and society – include some of the poorest neighborhoods in the region such as Watts, the port areas near Long Beach, and Van Nuys/Pacoima.

Is localized congestion associated with specific travel behavior patterns? More to the point, do people living in congested areas tend to make shorter or fewer trips? Table 2 includes mean volume-to-capacity (V/C) ratios for neighborhoods defined by trip-making characteristics of adults living within the region. For the Los Angeles basin as a whole, shorter trips and fewer trips are indeed associated with higher levels of congestion; the highest V/C ratio is associated with neighborhoods where individuals make fewer, shorter trips. This may not be surprising given that several of these neighborhoods are concentrated around downtown Los Angeles, which has relatively high congestion levels and relatively poor residents. However, the association between congestion and shorter trips in other, better-off neighborhoods may be evidence of individuals maximizing high levels of access to nearby opportunities despite, *or even because of*, congestion. In order to better understand these complex associations, we next examine them through a set of multivariate regression models.

4.2. Accounting for the individual

The data presented thus far show a spatial relationship between activity patterns and localized congestion. This descriptive analysis, however, does not control for socioeconomic and other demographic factors known to influence trip-making. The patterns in Table 1 also lead us to expect that traffic congestion, a phenomenon of on-road travel, may have a differential effect on trips by different modes and well as by income. To address these issues, we estimate a series of trip-making models that account for personal characteristics as well as individual travel behavior, travel mode, and localized congestion. Table 3

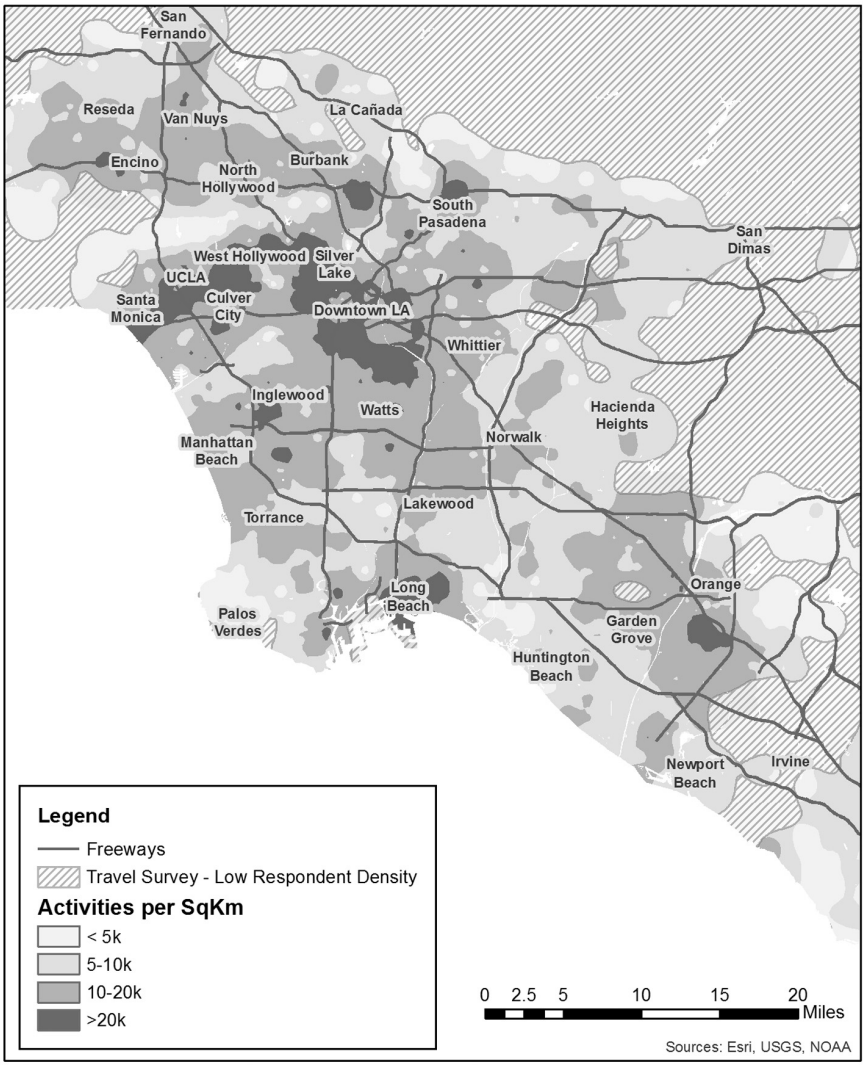

Fig. 3. Activity density across the region.

Table 2
Congestion levels and activity density, measured by trip-making behavior.

		Number of trips[a]	
		< 4 trips	4 trips or more
Trip distance[b]	< 6 km	0.84 V/C[c] 13,400 act./km^2	0.77 V/C[c] 11,000 act./km^2
	6 km or more	0.76 V/C[c] 10,800 act./km^2	0.69 V/C[c] 8600 act./km^2

[a] Compares areas with average trip rates above and below median number of trips (4 trips per day).
[b] Compares areas with average trip lengths above and below median trip length (6 km).
[c] Differences in mean congestion levels significant at $p > 0.05$ by ANOVA.

presents the results of a set of trip count (negative binomial regression) and trip likelihood (logistic regression) models, showing how congestion and individual trip-making behavior collectively vary with activity density throughout the region. Moran's I results for the deviance residuals in these models are reported in the Appendix A; we find no significant clustering or dispersion in our six models' residuals.

The first two models in Table 3 estimate the number of trips taken by any mode using negative binomial regression. Model 1 includes the sample of respondents living in traffic analysis zones (TAZs) with fewer than 10,000 activities per kilometer^2, as reported in the SCAG travel survey, and Model 2 includes those living in TAZs with > 10,000 activities per kilometer^2. A breakpoint of 10,000 activities per kilometer^2 divides the respondents into reasonably congruent sample sizes with a clear, memorable value. In addition to a local congestion term, the models include a term accounting for trip distance – the log of the respondent's mean trip length – as well as mode, included as a dummy variable for having walked or not on the survey day, and an interaction term between trip distance and having walked. We also explored versions of our models that included an interaction term between congestion and household income. However, that interaction term was not significant at the 95% confidence level in any of the models and we have therefore not included it in the models presented in Table 3. We also note that some coefficients and their significance raise intriguing questions, such as why trip-making by women may be significantly higher in low-activity density areas but not in high-activity density areas. This may reflect spatial differences in household structure or social norms, though additional data and analysis would be required to confirm this possibility.

For Models 1 and 2, as the trip length term decreases, trip-making goes up. Put another way, the models confirm that making short trips is a good way to make more trips, ceteris paribus (or, conversely, those who may need to make many trips may be inclined to make shorter trips). In Model 1 (low activity density areas), we find no significant

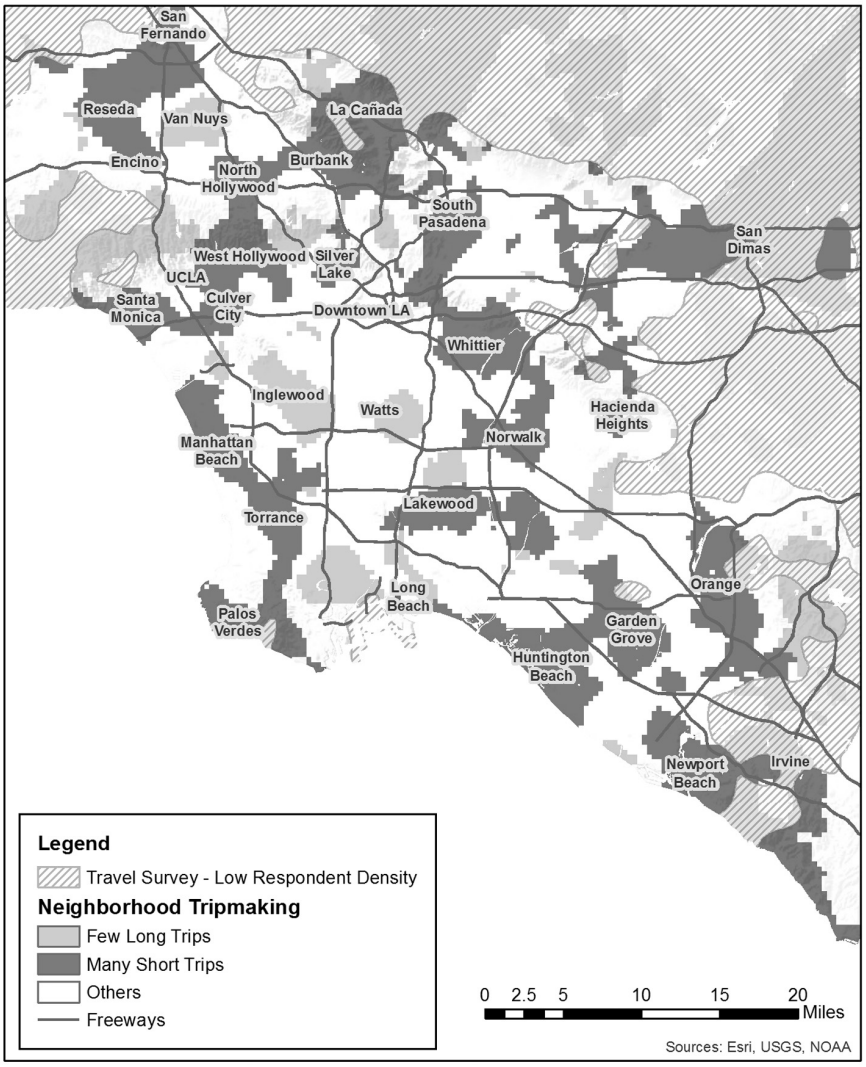

Fig. 4. Neighborhood trip-making tendencies: "Many Short" and "Few Long" trips.

effect at the $p < 0.05$ level for walking or the interaction term. However, we do find a significant effect for both terms in Model 2 (high activity density areas). While walking is associated with less trip-making, the interaction between walking and trip distance is positive and significant, suggesting that people who make long trips from dense, congested areas and who take at least one walk trip tend to make more trips overall. This result may reflect the value of walkable residential neighborhoods in facilitating personal trips, even when an individual must also make long trips during the day, such as for commuting. Consider, for example, a commuter living in dense, walkable West Hollywood who commutes to and from work in Long Beach, 50 traffic-congested kilometers away; despite the significant time expended and distance traversed for the journey to work, when the commuter returns home to destination-rich West Hollywood, the ability to walk to many nearby destinations facilitates increased activity participation.

Additionally, the effect of congestion on trip-making is not consistent between the first two models. In Model 1's relatively low-density areas, congestion has a significantly *negative* effect on number of trips made – as those who lament the ills of congestion would likely predict. However, in the denser areas covered in Model 2, local congestion has *no* (statistically significant) *effect*, either positive or negative, on trip-making rates. Other significant factors in Models 1 and 2 are reasonable, with additional students in the household and having a college-education consistently associated with more trip-making. In Model 1, being female is associated with increased trip-making, while working from home is negatively associated with trip-making.

Models 3 through 6 show the estimated effects of traffic congestion and other factors on travel mode using logistic regression. The related Fig. 5 shows the relationship between local congestion and the likelihood of traveling by car or on foot (with shaded 95% confidence bands around each of the estimates), holding all other model coefficients constant. Models 3 and 4 predict the likelihood of driving on the survey day, again separately examining areas below and above 10,000 activity destinations per kilometer^2, respectively. Model 3 (for low activity density areas) is weakly predictive, with only household income showing a significant, positive relationship to likelihood of driving in low density areas. In these areas, neither congestion nor trip distance show a significant relationship on likelihood of driving. However, Model 4 (for high activity density areas) shows a far different set of relationships. First, local congestion is significantly negatively correlated with likelihood of driving. Second, the significant positive correlation between trip distance and odds of driving suggests that cars are important for relatively long trips, but not necessarily all trips in these areas.

Models 5 and 6 predict the likelihood of walking on the survey day, again separately examining low and high (below and above 10,000 activity destinations per kilometer^2) activity density areas, respectively. Walking is associated with shorter mean trip lengths in both models, as

Table 3
Trip-making and localized congestion models.[a]

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Model type	Neg. binomial		Neg. binomial		Logistic		Logistic		Logistic		Logistic	
Dependent variable	Number of trips[b]		Number of trips[b]		Drove[c]		Drove[c]		Walked[c]		Walked[c]	
Activity density[d]	Low (< 10,000 activities/ km^2)		High (> 10,000 activities/ km^2)		Low (< 10,000 activities/ km^2)		High (> 10,000 activities/ km^2)		Low (< 10,000 activities/ km^2)		High (> 10,000 activities/ km^2)	
Predictor variables	IRR[e]	Prob.[f]	IRR[e]	Prob.[f]	OR[e]	Prob.[f]	OR[e]	Prob.[f]	OR[e]	Prob.[f]	OR[e]	Prob.[f]
Local congestion	0.858	0.032*	0.968	0.684	0.340	0.170	0.304	0.029*	1.627	0.329	2.952	0.034*
ln (mean trip dist.)	0.907	0.000*	0.885	0.000*	1.401	0.162	1.467	0.001*	0.538	0.000*	0.473	0.000*
Walked[c]	0.595	0.310	0.363	0.036*								
ln (MTD) × walked	1.106	0.080	1.169	0.004*								
Age	1.001	0.437	1.003	0.054	1.014	0.316	1.011	0.266	0.992	0.349	1.016	0.055
Students in Hhld.	1.072	0.000*	1.070	0.019*	1.021	0.884	0.909	0.390	0.791	0.042*	1.027	0.817
Hhld. income	1.000	0.224	1.000	0.260	1.000	0.074	1.000	0.000*	0.999	0.296	0.999	0.006*
English speaker	1.119	0.106	1.116	0.121	0.926	0.900	2.241	0.006*	0.928	0.893	0.469	0.015*
Female	1.164	0.000*	1.044	0.216	0.653	0.207	0.811	0.368	1.704	0.021*	1.372	0.122
White non-Hispanic	1.062	0.126	1.004	0.920	1.389	0.392	0.866	0.576	0.765	0.274	1.276	0.267
College-education	1.060	0.196	1.109	0.019*	1.439	0.322	1.873	0.009*	2.003	0.052	0.867	0.533
Job location												
At home	0.780	0.000*	0.905	0.209	0.873	0.833	0.563	0.215	0.584	0.145	0.959	0.894
Many locations	1.005	0.944	0.936	0.499	0.913	0.916	0.897	0.867	0.422	0.141	0.995	0.992
Constant	11.204	0.000	10.197	0.000*	0.853	0.946	0.182	0.198	28.298	0.006*	41.764	0.002*
N	1112		1341		1112		1341		1112		1341	
Wald chi-sq	202.02		159.78		17.45		62.51		56.61		80.47	
Prob. > chi-sq	0.000*		0.000*		0.095		0.000*		0.000*		0.000*	

[a] All models apply survey weights included with SCAG survey dataset. Adjusted R-squared value not supplied with survey weighted models.
[b] Number of trips taken on day of survey.
[c] Drove or walked (model dependent) at least once on survey day.
[d] Sample of respondents grouped by density of activities around their residential locations, greater or < 10,000 activities per kilometer^2 (median number for the entire weighted sample).
[e] To more easily interpret the unit effects of the independent variables on the dependent variable, incident rate ratios (IRRs) are reported for negative binomial regression coefficients and odds ratios (ORs) reported for logistic regression coefficients.
[f] Probabilities with asterisk are significant at least at the $p < 0.05$ level.

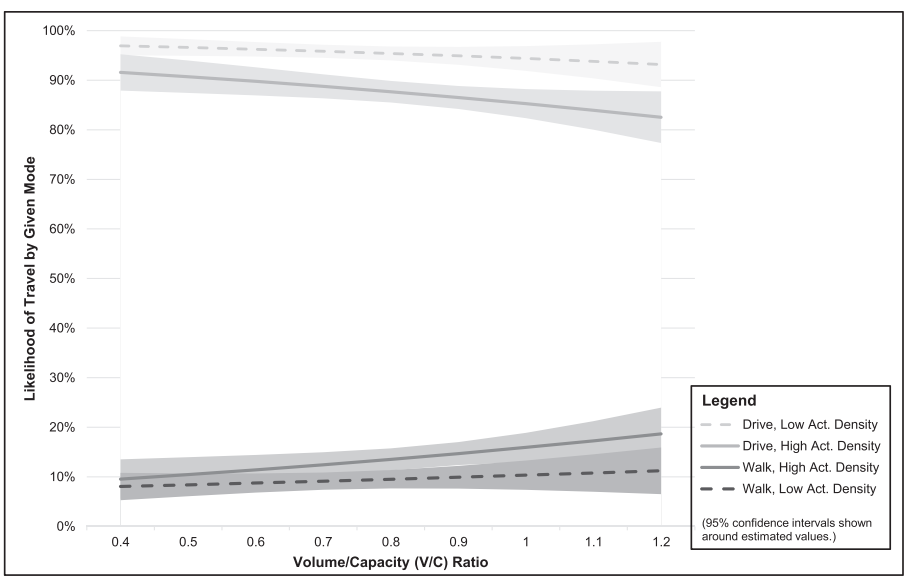

Fig. 5. Likelihood of traveling by driving or walking by local congestion level (V/C) and activity density (activities per km^2).

expected. In low activity density areas (Model 5), likelihood of walking has no statistically significant relationship to local congestion. But in high activity density areas (Model 6), congestion is positively associated with walking, suggesting that walking is a viable alternative to driving in congested, destination-rich districts.

Fig. 5 provides a straightforward means to visualize the model-estimated effects of congestion on mode choice. The differences between the two activity density groupings stand out starkly. In low density areas, odds of driving and walking stay relatively flat regardless of local congestion levels. In high activity density areas, by contrast, congestion is associated with a shift in mode choice, such that the likelihood of driving goes down and walking goes up as traffic increases.

Collectively, these models of trip-making and mode choice in low and high activity density areas paint a starkly contrasting picture of the effects of traffic congestion on activities and travel. In low activity density, more often outlying areas (see Fig. 3), congestion depresses trip-making, and has no effect on rates of driving or walking. By contrast, in high activity density, more often central areas, congestion has no statistically significant effect on trip-making, but decreases the odds of driving and increases the odds of walking. These latter, high activity density areas thus appear to be more congestion-adapted. In these places, it appears possible to cope, and even thrive, amidst chronic traffic congestion, provided that activity opportunities are proximate and viable alternatives to driving are available.

5. Conclusion

Even after accounting for the individual characteristics of travelers in our analysis, we find consistent, if nuanced, relationships between congestion and activity patterns. If one accepts that activity participation, operationalized here by trip-making, benefits individuals and society, our analysis suggests that road congestion should not be viewed solely, or even largely, as a cost to society because agglomerations of activities frequently give rise to traffic congestion – and these agglomerations enable high levels of activity participation, even in the face of congestion.

These data from Los Angeles show that residents of some areas enjoy high levels of accessibility and activity participation despite high levels of congestion, while in other areas congestion appears to contribute to lower levels of accessibility, as intuition would suggest. As a result, the picture of Los Angeles as a congested dystopia painted by metropolitan congestion measures like the TTI Mobility Index is misleadingly simplistic; the real story is far more nuanced, and interesting.

Because of congestion's paradoxical relationship to activity participation, people and firms may be better off in congestion-adapted neighborhoods, and worse off in congested-maladapted neighborhoods – even if the absolute levels of congested delays in both neighborhoods are similar. If so, standard measures of traffic delays – like V/C ratios or Levels of Service – on their own tell us next to nothing about whether the social and economic effects of congestion are benign or pernicious.

We emphatically do not argue that congestion causes more trip-making or that on its own is beneficial, but rather congestion is often an inevitable consequence of vibrant, thriving, agglomerated places. We wholeheartedly agree with many millions of drivers that traffic congestion is frustrating and irritating, but disagree with the premise of metrics like Level of Service that assume traffic delays on their own are necessarily problematic and costly – metrics that have been at the foundation of traffic impact analyses and development debates for decades. Instead, our analysis suggests that, in the right local conditions that promote both increased activity participation and perhaps increased congestion as well, a certain level of increased traffic delay associated with increased development may indirectly foster – or at least not discourage – patterns of trip-making and activity participation that benefit both individuals and society.

There is a movement afoot, spearheaded by planners seeking to increase the roles of biking and walking in urban travel, to develop more inclusive, multi-modal indicators of street and road performance that do not privilege vehicular movements over other forms of travel (Duncan et al., 2011; Lowry et al., 2012). The efforts of these planners to shift from an analytical focus on vehicular throughput are supported by our findings presented here. Indeed, shifting the units of analysis and focus away from (admittedly maddening) traffic delays on street networks, and onto how land use/transportation systems promote or discourage trip-making and activities in households and by firms will help planners and policy makers deliver greater benefits to travelers who so often find themselves stuck in traffic.

Acknowledgements

The authors are grateful for funding support from the U.S. Department of Transportation and the California Department of Transportation through the University of California Transportation Center. Thanks also go to the Southern California Association of Governments for providing the data used in this analysis. Any errors or omissions are the responsibility of the authors alone. In addition we thank Steven Brumbaugh and Herbie Huff for their contributions to this project.

Appendix A

Moran's indices for independent and dependent variables, model residuals

	Moran's I	Z-score	Prob.
Number of daily trips	0.0056	0.3258	0.7446
Walked that day (Yes/No)	0.0211	1.1700	0.2419
Drove that day (Yes/No)	0.0090	0.5160	0.6059
Localized congestion	0.8452	45.828	0.0000*
Household income	0.0887	4.8304	0.0000*
Ln (mean distance of daily trips)	0.0426	2.3314	0.0197*
Age	0.0646	3.5231	0.0004*
Number of students	0.0534	2.9176	0.0035*
English-speaking (Yes/No)	0.0524	2.8665	0.0041*
Gender (Male/Female)	− 0.0086	− 0.4432	0.6576
White (Yes/No)	0.2475	13.429	0.0000*
College-educated (Yes/No)	0.1039	5.6540	0.0000*
Number of job locations	0.0079	0.4495	0.6531
Activity density	0.8250	44.906	0.0000*
Model 1: deviance residuals (trip count NB, activity density < 10,000 psqmi)	0.0053	0.2145	0.8301
Model 2: deviance residuals (trip count NB, activity density > 10,000 psqmi)	− 0.0324	− 1.270	0.2039
Model 3: deviance residuals (driving logit, activity density < 10,000 psqmi)	− 0.0345	− 1.181	0.2376
Model 4: deviance residuals (driving logit, activity density > 10,000 psqmi)	0.0060	0.2693	0.7877
Model 5: deviance residuals (walking logit, activity density < 10,000 psqmi)	− 0.0186	− 0.6167	0.5374
Model 6: deviance residuals (walking logit, activity density > 10,000 psqmi)	0.0270	1.113	0.2657

* Significant spatial dispersion or clustering at $p < 0.05$.

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