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Heightening Walking above its Pedestrian Status: Walking and Travel Behavior in California

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Heightening Walking above its Pedestrian Status: Walking and Travel Behavior in California

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DISCLAIMER STATEMENT

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Executive summary

People walk a lot—to walk pets, to exercise and recreate, and to access public transit and local shops. Walk trips begin and end almost every journey, even trips made by automobile. Data from the current California Household Travel Survey (CHTS) show that walking occurs more than trips by both transit and bicycle, making it the second most common travel mode in California. Yet outside of select case studies in specific metropolitan areas, we know very little about walking behavior in California. An improved understanding of the determinants of walking will aid efforts to reduce driving and achieve greenhouse gas emission reduction targets.

In this study we draw on data from the last two California Household Travel Surveys to examine walking behavior in four major California regions—the San Francisco Bay Area, Los Angeles, Sacramento, and San Diego. The study includes four components; analyses of (a) the change in walking over time (b) the relationship between walking and the built environment (c) the determinants of change in walking over time and (d) the relationship between changes in neighborhood characteristics and changes in walking. In each of the analyses, we pay particular attention to differences across these four metropolitan regions. We pair our statistical analysis with a set of interviews intended to understand whether and how walking trips are included in regional travel demand models.

We find that, although walking remains a relatively small share (9%) of trips within the study area, walking rates have increased dramatically over time. The share of trips by walking grew almost twofold since 2001; from 5 percent to 9 percent. Moreover, while the share of walking trips is relatively small, walking mode shares are nine times higher than the percentage of trips taken by public transit or bicycle.

We further find that the decision to walk can be explained by a number of different factors including characteristics of the person, household, trip, and built environment as well as the region in which the trip occurs.

We find that built environment characteristics are positively related to both (a) walking mode share and (b) changes in walking mode share over time. However, compared to other factors, built environment characteristics have a relatively small effect on walking, a finding that is consistent with other walking studies. However, our data also show that the characteristics of neighborhoods are slowly changing over time in ways that are conducive to walking, for example increasing housing and employment densities. Further, there is a strong relationship between walking and trip distance, which also is influenced by the built environment, particularly the quantity and quality of very local destinations.

With respect to the interviews, we find that most Metropolitan Planning Organizations (MPOs) have shifted to activity-based models, which are better suited to understanding walking compared to the traditional 4-step model. However, these models can be enhanced to improve their attention to and treatment of walking. There remains a mismatch between the goals of travel demand models (largely focused on the supply and demand for travel as represented by the highway and transit network) and walking. Additionally, travel demand modelers lack high quality, longitudinal data on the pedestrian volumes, flows and the pedestrian environment.

Combined, our analysis provides the basis for a set of recommendations to encourage walking and to better incorporate walking in future data collection efforts and regional travel demand models. These include:

1. A focus on increasing intersection densities and providing better pedestrian route directness.
2. Targeting changes in the built environment to population groups that already exhibit relatively high rates of walking. These changes might include addressing safety and crime issues as well as other issues affecting the pedestrian environment in low-income and immigrant neighborhoods where a disproportionate number of households do not own automobiles. Future developments may also involve improving the proximity of family- and child-oriented amenities, such as high-quality schools and childcare facilities, which may increase opportunities for walking by members of households with young children, who are already more inclined to walk than their peers.
3. Adopting planning efforts to provide very local access (within a ½ mile) to important destinations (e.g. parks, gyms, and other fitness venues, restaurants, cultural institutions, and schools).
4. Collecting additional data on (a) walking behavior, (b) pedestrian volumes and location, and (c) the pedestrian environment over time.

I. One step at a time: Introduction

Walking is an important travel mode. As numerous scholars have shown, walking can potentially contribute to positive health outcomes, promote social interaction, and enable access to opportunities particularly among individuals who cannot drive (Kuzmyak, Baber, & Savory, 2006). Walking also has the collateral benefit of having a small environmental footprint, potentially helping to relieve congestion and global warming. Finally, walking is an important mode because it is a significant way in which people travel. After automobile trips, walking is the second most common travel mode. According to data from the 2001 National Household Travel Survey (NHTS), there were more than 42 billion walk trips per year comprising more than 10 percent of all trips in the US (Agrawal & Schimek, 2007).

Despite its prevalence, walking tends to be one of the most understudied modes of travel (Krizek, Handy, & Forsyth, 2009). One reason for this may be the difficulty in obtaining suitable data. National travel surveys, such as the NHTS, tend to systematically underreport walk trips (Agrawal & Schimek, 2007; Clifton & Krizek, 2004). Moreover, the sample sizes for national surveys do not lend themselves to detailed analysis of specific cities and neighborhoods, since it is rare for more than a very few households from the same neighborhood to be included in the survey sample. While data from the Decennial Census and the American Community Survey allow for more fine-grained spatial analysis, they only contain data on walking as part of the journey to work (Plaut, 2005). Among all walk trips, only four percent are taken as part of the trip to or from work; in comparison, almost 50 percent of walk trips are related to shopping, errands, and personal business (Agrawal & Schimek, 2007). Consequently, existing studies tend to rely on regional travel survey data; see, for example, studies on Atlanta (Frank, Kerr, Sallis, Miles, & Chapman, 2008); Austin (Cao, Handy, & Mokhtarian, 2006); the Twin Cities (Forsyth, Hearst, Oakes, & Schmitz, 2008; Forsyth, Oakes, Schmitz, & Hearst, 2007); the Bay Area (Agrawal, Schlossberg, & Irvin, 2008; Cervero & Duncan, 2003); Portland (Agrawal et al., 2008); and urbanized King County, Washington (Lin & Moudon, 2010; Moudon et al., 2007).

The existing body of research suggests that the amount of walking is influenced by a host of factors including: individual and household characteristics, trip purpose and time, and characteristics of the built environment.

Individual and household characteristics: Most studies show that individual and household characteristics are the most influential characteristics in predicting walking behavior (Cervero & Duncan, 2003). For example, lower-income walkers tend to walk more for utilitarian trips (shopping and social events) and less for recreation compared to higher-income walkers.

Trip characteristics: Trip distance and purpose also influence the decision to walk. For transit planners, distances of up to a half mile are commonly considered to qualify as "walking distance" (Guerra, Cervero, & Tischler, 2012). According to data from the National Household Travel Survey, the mean and median walk distance in the U.S. are 0.7 and 0.5 miles respectively (Yang and Diez-Roux, 2012). Walk trips are a common part of the travel behavior of transit commuters because walking is the predominate mode of access to transit (Lachapelle & Noland, 2012). People also walk for other types of local trips including trips for shopping, recreation, and to walk pets (Handy & Clifton, 2001; Santos, McGuckin, Nakamoto, Gray, & Liss, 2011).

Built environment: There is a growing scholarship on the relationship between walking trips and the built environment (see Handy, 2005; Owen et al., 2004; Saelens & Handy, 2008; Saelens, et al., 2003 for reviews of the literature). Overall the findings from these studies are mixed. Early research by Cervero and Radisch (1996) suggests that walking trip demand is more elastic than the demand for commute trips; the choice to make trips by foot, therefore, would be more sensitive to neighborhood characteristics and rates of vehicle ownership. Indeed, some scholars find that walking is more likely to occur in high-density neighborhoods where there is a mix of land uses (Badland & Schofield, 2005) and origins and destinations are proximate (Agrawal & Schimek, 2007; Badland & Schofield, 2005; Handy, 2005; Saelens et al., 2003). Other scholars find that while built environment characteristics are associated with walking trip purpose and location, they are not associated with how much people walk (Forsyth et al., 2008, 2007; Oakes, Forsyth, and Schmitz, 2007). Finally, the relationship between the built environment and walking varies across population groups (Forsyth et al., 2009) as well as neighborhood types (Blumenberg et al., 2015; Ralph et al., 2016; Voulgaris et al., forthcoming).

In this report, we extend the existing body of scholarship on walking by analyzing data from the 2001 and 2012 California Household Travel Survey (CHTS), a sample of some 42,000 households in the state. We examine walking in the four largest urbanized regions—the Bay Area, Los Angeles, Sacramento, and San Diego—areas that comprise approximately 60 percent of the state's population. See Map 1 for the location of our study area.

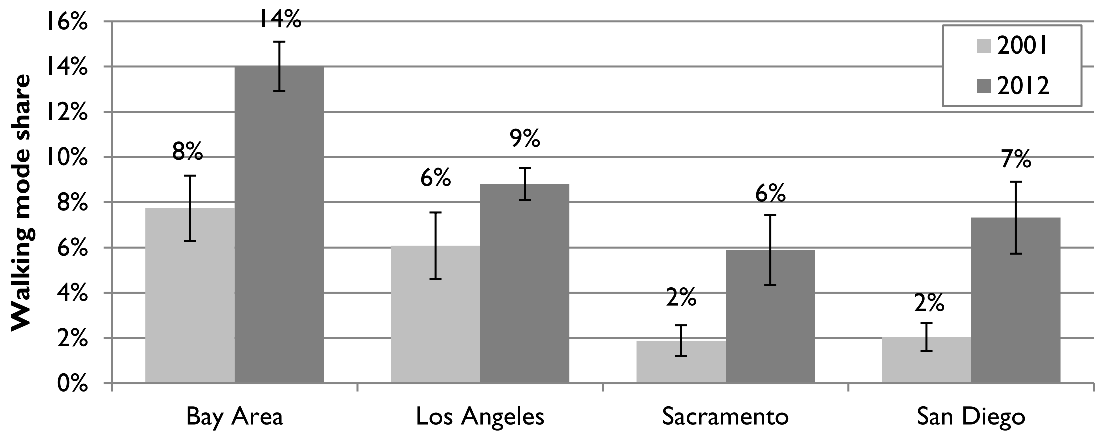
Map 1. Study area: Bay Area, Los Angeles, Sacramento, San Diego

Our analysis centers on explaining changes in walking over time and, in particular, the role of the built environment as a determinant of change. We analyze the percentage of trips taken by walking. To assemble a data set that is consistent between the two survey years, we analyze linked trips, defined as a change in location with the purpose of participating in non-travel activities. Walk trips are defined as those for which all segments took place by walking.

In our study areas, walking increased substantially from 2001 to 2009 from 5 percent of all trips to 9 percent. As Figure 1 shows, walking rates rose across all four metropolitan areas; however, the rate of increase varied by region. In both time periods, walking rates were highest in the Bay Area. However, Sacramento and San Diego experienced the greatest increases in walking over this period.

We pair our statistical analysis with a set of interviews intended to understand whether and how walking trips are included in regional travel demand models.

Figure 1. Increase in walking mode share by metropolitan area – 2001 to 2012



More specifically, this research addresses the following five questions:

1. Have walking rates changed over time?
2. What are the determinants of walking and, in particular, is there a relationship between the built environment and walking?
3. What explains the change in walking over time?
4. Is there a relationship between changes in neighborhood characteristics and changes in walking?
5. How can walking be better incorporated into regional travel demand models?

The following bullet points summarize our major findings and are organized around the above research questions:

Walking

- Walking rates increased over time. As we note above, the share of trips by walking grew almost twofold from 2001 to 2012 from 5% to 9%. Over this time period, the rate of change was highest in Sacramento and San Diego; however, walking rates were highest in the Bay Area in both survey periods.

- Walking remains a relatively small share (9%) of all trips. However, this percentage is nine times higher than the percentage of trips taken by public transit or bike.

- Walking rates are highest among those without driver's licenses, adults with children ages 5 to 12, non-workers, and immigrants. They are also highest in very dense urban areas and, among our study areas, in the Bay Area.

- From 2001 to 2012, walk trip distances declined from .9 miles to .5 miles.

- The 2012 travel survey is large and appears to have captured a significant number of walk trips. In comparison, however, the sample of walk trips in the 2001 survey is relatively small. Moreover, trip data in the two surveys were assembled differently, complicating analyses of change over time.

Determinants of Walking

- Like other studies, we find that walking can be explained by a number of different factors including characteristics of the individual, household, trip, and the built environment as well as geographic location (in this case, residential location in one of the four metropolitan areas in our study).

- There is a positive and statistically-significant relationship between walking and the built environment.

- The built environment has a relatively small effect on walking compared to other factors such as individual, household, and trip characteristics (e.g. distance and purpose). Trip distance is a function of having proximate destinations and is therefore related to the built environment.

- Factors with a strong association with walking include: trip distance, trip purpose (particularly for home-based fitness trips), and the absence of a driver's license.

Explanations for the Change in Walking over Time

- Observed changes in the built environment are positively associated with changes in walk rates over time.

- There are two types of built environment effects: (a) changes in the characteristics of the built environment toward environments conducive to walking and (b) changes in the effect of the built environment on the likelihood of walking.

- Characteristics of the neighborhood (density, age of housing stock, percent youth) are associated with walking. The magnitude of their effects has remained constant over time.

- Neighborhood characteristics have a relatively small effect on changes in walking compared to other factors such as (a) individual, household, and trip characteristics and (b) changes in the magnitude of their effect on walking.

- Trip characteristics (trip distance and purpose) have the greatest effect on the likelihood of walking; the magnitude of these effects has increased over time.

- There is a lack of built environment data by neighborhood over time. Consequently, the analysis relies on a limited set of neighborhood characteristics included in the U.S. Census.

Changes in Neighborhood Characteristics and Changes in Walking

- Changes in neighborhood characteristics are associated with changes in walking.

- The poverty rate is negatively related to walking; an increase in poverty is associated with a decline in walking mode share.

- Intersection density is positively related to walking; an increase in the number of intersections per acre is associated with an increase in walking mode share.

- The ability to construct longitudinal analyses of walking is limited by the small sample size of the 2001 household travel survey as well as the lack of built environment data by neighborhood over time.

Walking and Regional Travel Demand Models

- Most of the Metropolitan Planning Organizations (MPOs) that are responsible for regional transportation planning within our study areas have shifted to activity-based models, which are better suited to understanding walking compared to the traditional 4-step model.

- Notable issues and gaps still exist including (a) a mismatch between the goals of travel demand models (largely focused on the supply and demand for travel as represented by the highway and transit network) and walking and (b) the lack of high quality, longitudinal data on the pedestrian volumes, flows and the pedestrian environment, sidewalks specifically.

The analysis has a few shortcomings that are important to note. First, there are some data limitations that constrained our analysis including a relatively small sample size in 2001, inconsistencies in the reporting of walk trips between the two survey years, and the lack of longitudinal data on the built environment of neighborhoods. Second, there is a self-selection bias related to residential location. Some respondents who are inclined to walk also may be more likely to live in "walkable neighborhoods." Studies show that controlling for residential self-selection tends to diminish, but not eliminate, estimates of the effects of the built environment on travel behavior (Cao et al., 2006; Ewing & Cervero, 2010; Handy, Cao, &

Mokhtarian, 2005; Mokhtarian & Cao, 2008; Zhou & Kockelman, 2008). Further, Levine et al. (2005) argue that residential self-selection is one of the means by which the built environment can influence travel behavior, especially if particular types of built environments are undersupplied. Finally, while we find a relatively small relationship between the built environment and walking, travel distance has a strong effect on walking and also is strongly associated with characteristics of the built environment, particularly local access to opportunities.

The findings of this study suggest the following recommendations, which we highlight in greater detail in the conclusion in each of the subsequent chapters.

1. The data suggest that planners can facilitate walking by emphasizing increased intersection densities and providing better pedestrian route directness. However, substantial increases in walking can only occur with equally substantial changes in the built environment.

2. Changes in the built environment targeted to population groups that already exhibit relatively high rates of walking also may increase walking. These changes might include addressing safety and crime issues in low-income neighborhoods where a disproportionate number of households do not own automobiles. They may also involve improving the proximity of family- and child-oriented amenities, such as high-quality schools and childcare facilities, which may increase opportunities for walking by members of households with young children, who are already more inclined to walk than their peers.

3. Walk trips tend to be short. Therefore, planning efforts to provide very local access (within a ½ mile) to important destinations (e.g. parks, fitness venues, schools, cultural institutions, etc.) would increase the likelihood that some of these trips are taken on foot.

4. Additional data are needed on (a) walking behavior, (b) pedestrian volumes and location, and (c) the pedestrian environment over time to support future analyses of travel behavior as well as regional travel models. Larger sample sizes are important, particularly since a relatively small percentage of trips are walk trips. Moreover, the data ought to be collected and assembled consistently over time to facilitate longitudinal analyses.

We organize this report as a set of separate analytical chapters. In Chapter Two, we analyze data from the 2012 CHTS to examine the relationship between walking and the built environment. Working with the most recent data allows us to associate the microdata data

(data on trips and the individuals who make them) with a full complement of built environment characteristics (including data on the pedestrian environment from Walk Score®).[1] In Chapter Three, we aggregate data from the two travel surveys to examine the determinants of change in walking over time. In Chapter Four, we shift the unit of analysis from the trip to the census tract. In this chapter we explore the relationship between changes in the characteristics of census tracts and changes in walk rates over time. Finally, in Chapter Five, we report on the findings from our interviews with planners and regional travel demand modelers. Each chapter includes an associated literature review, discussion of methodology, and a set of policy recommendations.[2] Additional analyses and data including tables and maps by region and county are included in the Appendices.

[1]Data provided by Redfin Real Estate https://www.redfin.com

[2]This report structure helps to explain why the content of the literature review in each of the analytical chapters overlaps.

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II. Are these streets made for walking? Walking and the built environment in California

Introduction

Planners, environmentalists and public health officials hope that by refashioning America's roadways to encourage pedestrian activity, cities will experience a plethora of social and environmental benefits. Their premise is that cities where more people walk to complete their daily activities will be full of healthy people, thriving businesses and socially-connected neighborhoods. Although it is difficult to isolate causality, a growing body of research shows relationships between walking and pedestrian-friendly neighborhoods and a number of outcomes measures including lower obesity rates (Frank et al., 2004; Murphy et al., 2007), higher property values (Pivo & Fisher, 2011; Rauterkus & Miller, 2011), increased social capital (Leyden, 2003; Rogers et al., 2011), improved quality of life (Talen 2002; Jaśkiewicz & Besta, 2014), and better access to opportunities (Cerin et al., 2007).

Given the many purported benefits of walking, urban planners have championed "walkability" through a variety of infrastructure projects and initiatives. The names, Great Streets, Safe Streets, Complete Streets, and so on, convey the enthusiasm of planners for creating more walkable neighborhoods. However, specific definitions of and measures of walkability are needed if we are to evaluate the success of these efforts. While there is no shortage of possible measures of walkability — the search for a single walkability measure is frustrated both by the multi-dimensional character of the built environment and a lack of readily available built environment data for all possible scopes (e.g. for national, regional, or local studies), scales (e.g. with data measured at the city, neighborhood, or parcel level), and time periods.

The purpose of this analysis is to identify the relationships between several walkability measures and to determine the degree to which such measures predict the likelihood of walking. We draw on data from the 2012 California Household Travel Survey to determine how walking varies within California's four major metropolitan areas —the Bay Area, Los Angeles, Sacramento, and San Diego— and compare this distribution to that of various measures that have been proposed by researchers to quantify walking behavior. We then estimate a logistic regression model to determine how well these measures of the built environment predict the likelihood that a trip will take place by walking, controlling for trip, individual, and household characteristics.

Our analysis is organized as follows. We first examine existing research on the factors influencing travel behavior generally and the choice to walk more specifically. Following this review, we present descriptive statistics on differences in walking across urban areas and neighborhood types. As might be expected, there is more walking in the San Francisco region and in "old urban" areas, neighborhoods with very high-densities and transit supply. We then estimate a trip-level model to identify the factors related to the likelihood a trip will be completed by walking, controlling for individual, household, trip, and built environment characteristics and geographic location (e.g. metropolitan area).

Our findings suggest that all these factors influence the choice to walk. However, individual, household and regional variables influence the choice to walk to a much greater degree than built environment factors, a finding consistent with other research on this topic. We suggest policymakers, planners and engineers recognize some groups are more likely to take walk trips than others and consider prioritizing areas where these people live for improvements to the walking environment.

Literature review: Walking and the built environment

Neighborhood and built environment characteristics influence travel decisions and behavior. In their meta-analysis of existing literature on this topic, Ewing and Cervero (2010) find that built environment variables have an inelastic relationship with most travel outcomes. With respect to walking behavior, the variables with the largest effects include diversity of land use, access to destinations and intersection density. Nevertheless, they conclude that in concert, multiple built environment variables may exhibit large effects on walking behavior even after accounting for socio-demographic characteristics. Their analysis builds on several previous studies which consider the individual and sometimes overlapping components of the built environment that affect travel behavior, such as density, diversity (of land use), design, destination accessibility, distance to transit, and pedestrian amenities (An & Chen 2009; Cervero & Kockelman, 1997; Ewing & Cervero, 2001, 2010; Ewing & Handy, 2009; Mathews et al., 2009).

The goal in studying each of these individual components is to determine which environmental aspects encourage or dissuade walking. In some cases, specific measures—employment density, residential density, or distance to commercial businesses—serve as proxies for these dimensions. We briefly discuss these measures in turn below.

Density

Many studies report a strong positive correlation between various measures of density and walking outcomes: population density (Agrawal & Schimek, 2007; Forsyth et al., 2008; Greenwald & Boarnet, 2001; Kim & Susilo, 2013); employment density (An & Chen, 2009; Wang, 2012); and residential density (Rajamani et al., 2003). The relationship between density and walking behavior is likely nonlinear (Christiansen et al., 2016). Density of a certain magnitude may provide, what Forsyth et al. (2008) refer to as, a "critical mass" to energize street life with people walking. But, critical density is unlikely achieved without many of the other built environment characteristics also known to encourage walking trips. Therefore, density variables run the risk of overlapping with other built environment variables, in particular, proximity to destinations and diversity of land uses. When considering density as a walking determinant, an aptly mentioned question in Forsyth et al. (2008) asks: "Once this critical mass of land use variety has been reached, will more mix matter?" Moreover, an increasing number of destinations, density and diversity of land-use could eventually lead to diminishing returns (Christiansen et al., 2016). At some threshold, increased density may produce negative effects such as congestion that may influence affect modal decisions.

Proximity to destinations

Do people walk more when there are nearby places to go? In California, more than 25 percent of California Household Travel Survey respondents reported that the greatest barrier to walking was having "no place interesting to go" (McGuckin, 2012). Thus, it would seem likely that increased proximity to desirable places (shopping, restaurants, parks, etc.) would motivate individuals to make more walking trips. This assumption is supported by many scholars who find a relationship between walking trip frequency, population density *and* destination proximity (Handy et al., 2006; Kim & Susilo, 2013; McGuckin, 2012; Saelens & Handy, 2008). These factors are likely interrelated: proximity to destinations increases with density and vice versa (Saelens & Handy, 2008). Perceived proximity may also affect walking. Handy et al. (2006) find a positive correlation between both perceived and objective proximity to destinations and walking.

Proximity to certain types of destinations may matter more than others. Are people more likely to walk to a nearby transit stop than to school? Some studies examine the relationship between walking and proximity to shopping districts (as well as the spatial distribution and number of shopping destinations within an area). However, existing research does not address which destination types are most strongly correlated with walk trips.

Diversity of land use

Areas with higher density and more proximate locations likely have a more diverse mix of land uses; therefore, the mix of land uses may also be relevant in the relationship between walking frequency and density (Kim & Susilo, 2013). A number of studies find a positive correlation between mixed-land uses and walking or non-motorized travel (Forsyth et. al., 2008; Kim & Susilo, 2013; Rajamani et al., 2003).

Street connectivity

The connectivity of street networks, or "directness or ease of travel between two points" also emerges as a feature of the built environment pertinent to walking (Forsyth et al., 2008a-quoted Saelens et al., 2003). Streets are commonly aligned in a gridiron pattern in older cities and neighborhoods. This pattern gives rise to smaller blocks, more intersections, and shorter distances from one intersection to the next. Conversely, newer or suburban environments typically comprise neighborhoods with branching street networks and intersections. These street connectivity patterns, or typologies, have been used as a proxy for urban sprawl (Barrington-Leigh & Millard-Ball, 2015).

Many researchers posit that the number of linkages between streets or connections induce walking. Wang (2012) measures connectivity as the density of four-way intersections and finds a positive relationship with non-motorized trips. Ewing and Cervero (2010) find a higher average elasticity between intersection and street density than other design variables. Interestingly, they find a negative elasticity associated with percentage of four-way intersections. They note that this measure of connectivity does not fully account for block length, which they believe explains the discrepancy. Finally, Oakes et al. (2007) use block size as measure for connectivity and find an increase in leisure walking with no effect on travel walking. The connectivity results, thus, appear mixed, although they do represent a worthy attempt to quantify discernable patterns in urban design.

Barrington-Leigh and Millard-Ball (2015) suggest average nodal degree as a useful measure of street connectivity and as a proxy for sprawl. Average nodal degree is the average number of legs at each intersection within an area (such as a census block group or tract). For example, the end of a cul-de-sac has a nodal degree of one, and a four-legged intersection has a nodal degree of four[3]. Neighborhoods with the highest average nodal degree are those with dense grid networks and few dead-ends.

[3]See Appendix C for a detailed and graphic representation of this concept.

Walkability composite measures

No single measure of the built environment appears to have a predominant or "magical" influence on people's choice to walk. Rather, certain characteristics in combination create places where people are likely to walk. Various researchers have devised or used composite measures of walkability to capture multiple characteristics of the built environment; these include Walk Score® (Foti & Waddel, 2014; Manaugh & El Geneidy, 2011; Weinberger & Sweet, 2012), neighborhood typologies (Blumenberg et al., 2015; Voulgaris et al., forthcoming), walkability index (Frank et al., 2005), and Sprawl Index (Hamadi et al., 2015).

Walk Score® is a commercial product that rates neighborhoods on a scale from 1-100 of walkability, from "car-dependent" to "walker's paradise."[4] The algorithm counts destinations across a number of categories (shopping, culture, dining, etc) by their distance and then penalizes places with low population density or intersection connectivity. A number of studies have tested the reliability of Walk Score® and find it to be correlated with components of neighborhood walkability including street connectivity, access to public transit, and residential density (Carr et al., 2010; Duncan et al., 2012).

Weinberger and Sweet (2012) find that Walk Score® is a reasonable predictor of walking behavior, and can successfully be used to model the likelihood of walking across various trip purposes. Their analysis also suggests that threshold effects exist with respect to Walk Score®; the largest gains in walking trips occur between Walk Scores® of 50 and 100.

Manaugh and El-Geneidy (2011) compared multiple walkability indices, including Walk Score® and walkability index, and their effectiveness in predicting walking behavior across various trip purposes. They find, and are supported by later work by Koschinsky et al. (2016) that walkability indices have a greater impact on wealthier and larger households. In other words, elasticities are much higher for these groups, and relatively inelastic for low-income individuals. This finding is consistent with other research concluding that socioeconomic factors have the largest influence on a person's likelihood to make a walk trip (Ewing & Cervero, 2010; Ewing et al., 2014; Handy & Clifton, 2001). Public health researchers have used Walk Score® to examine the relationship between walkability and obesity rates (Wasserman et. al, 2014).

[4]Data were provided by Redfin Real Estate, https://www.redfin.com

Blumenberg et al. (2015) and Voulgaris et al. (forthcoming) apply factor analysis and cluster analysis to develop a categorical composite measure of the built environment. They classify census tracts in the United States into one of seven distinct neighborhood types: Rural, New Development, Patchwork, Urban Residential, Old Urban, and Mixed Use (or Job Center). Of these, they find that "New Development" neighborhoods are the most car-dependent and "Old Urban" neighborhoods are the least car-dependent.

Transportation versus leisure walking

Some environmental features that are conducive to utilitarian walk trips (e.g. proximity to destinations) may not be conducive to recreational walk trips. For example, Lee and Moudon (2006) find an inverse relationship between the presence of "hills" and recreational and utilitarian walking. "Hills" may be related to more walking for recreation but less walking for transport. Additionally the presence of transit, sidewalks, streetlights and connected land uses (among others) appear to have negative associations with recreational walking but are positively related to utilitarian walking (Forsyth et al., 2008). Therefore, trip purpose, at least in terms of utilitarian versus recreational purposes, should be considered when understanding the determinants of walking behavior. Other scholars suggest that walking for transportation may actually replace walking for recreation, an idea referred to in public health and other literature as an "activity budget" (Forsyth et al., 2008; Oakes et al., 2007). The concept behind the activity budget is that, as with time, individuals make tradeoffs depending on how much total activity they deem necessary. A person may forgo their recreational walk around the neighborhood for a walk to work or school, and vice versa.

Data and descriptive analysis

We draw on the built environment and walking literature in assembling our analysis of walking in California's large metro regions. The 2012 California Household Travel Survey (CHTS) is the primary data source for this study. Conducted by the California Department of Transportation, the CHTS collects travel data on an approximate ten-year cycle from households throughout California. Members of participating households completed travel diaries with detailed information about all trips and activities during a pre-assigned 24-hour period, where dates were assigned to ensure that data were collected for every day for a full year. Upon completing the travel diary, survey participants reported their travel through a computer-assisted telephone interview or by returning the travel diaries by mail.

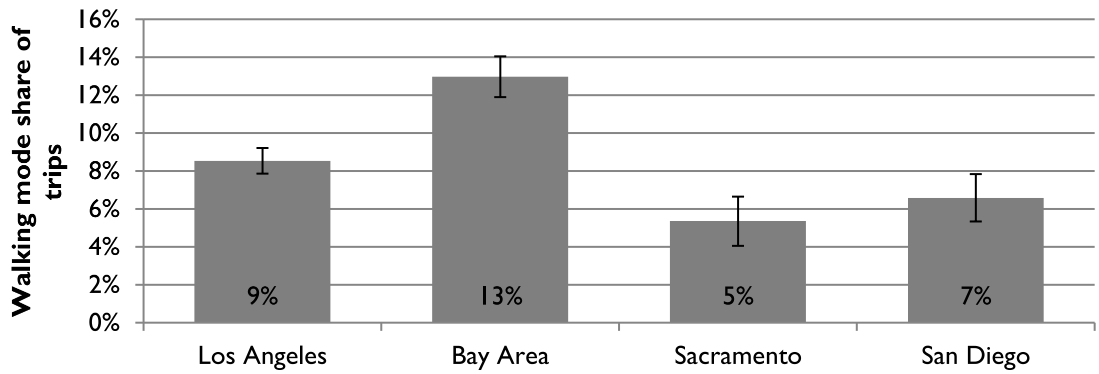
Our analysis is limited to adult survey respondents living in one of California's four major metropolitan areas: the Bay Area (San Francisco, Marin, San Mateo, Contra Costa, and Alameda counties), Los Angeles (Los Angeles and Orange counties), Sacramento (Sacramento, Placer, El

Dorado, and Yolo counties), and San Diego (San Diego county) (see Map 1) . These regions and their component counties make up more than 60 percent of the state's population (California Department of Finance, 2016). Since the study focuses on intra-metropolitan travel, we exclude from our analysis any trips that were longer than 150 miles.

Also, the study centers on utilitarian trips where the primary mode was walking. Thus, a trip is defined as a change in location with the purpose of participating in non-travel activities. However, the 2012 CHTS also includes information on trips with a purpose of changing transportation modes (walking to a transit station or a remote parking location, for example) as well as loop trips (for instance, going on a walk for exercise, where the trip begins and ends in the same location). In order to limit our analysis to utilitarian walk trips, we removed all loop trips from the data set and linked all mode-changing trips together to identify the trips' ultimate origins and destinations. Walk trips are defined as trips for which all segments took place by walking.

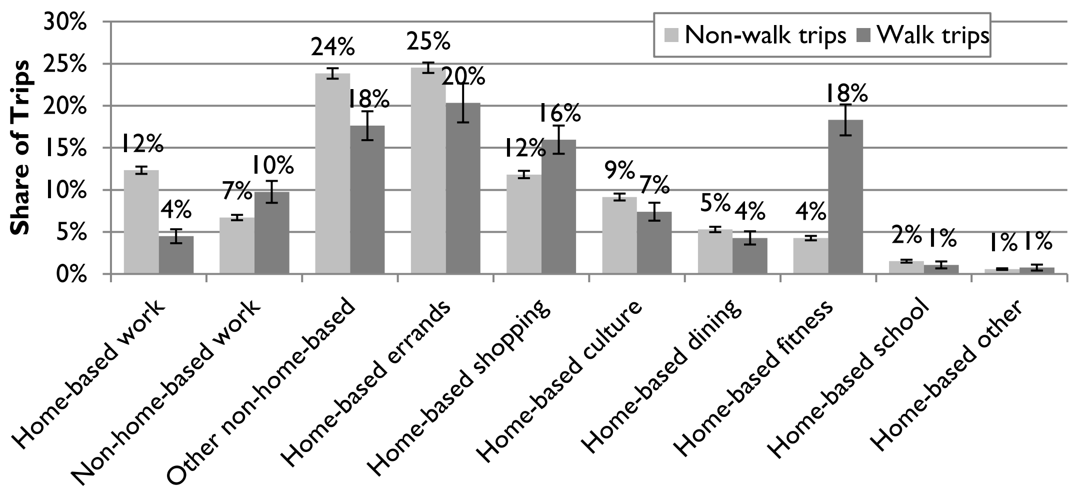
Figure 2 shows how the walking mode share differs by metropolitan region. In this and other figures throughout this paper, error bars indicate 95-percent confidence intervals. Walking is highest in the Bay Area (13%) and lowest in Sacramento (5%).

Figure 2. Walking mode share by MSA



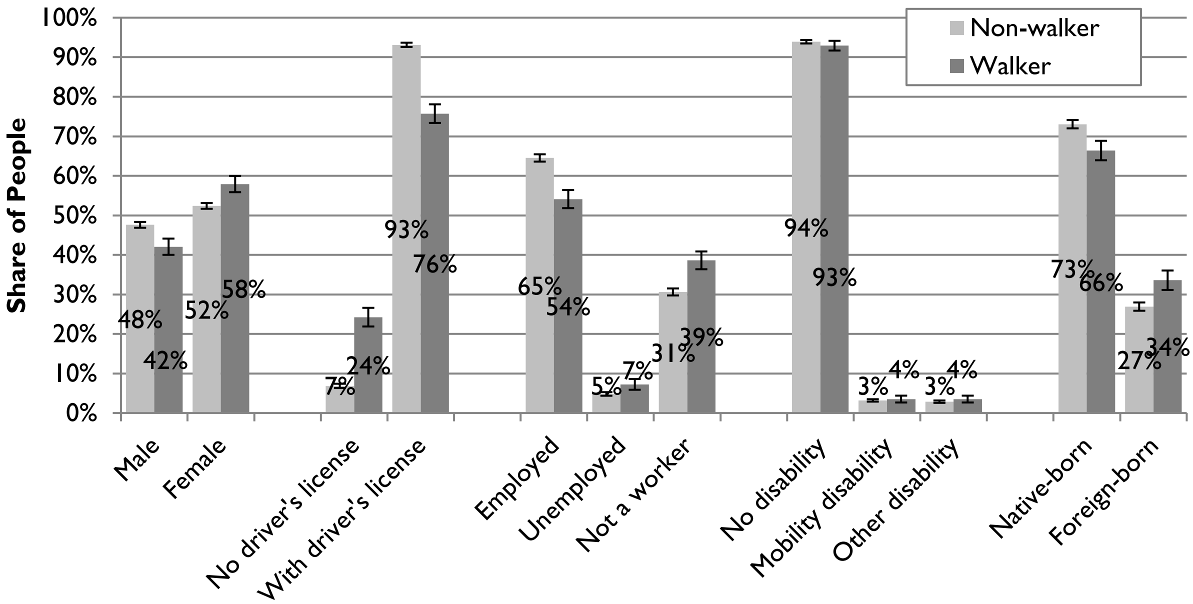
For the purposes of this analysis, we defined ten different trip purpose categories, which we differentiated based on activities at trip origins and destinations. Most of these categories are self-explanatory. Home-based fitness trips are not loop trips (such as recreational walks or bike rides that begin and end at home), but rather trips to a location for fitness activities, such as a gym, a fitness class, or a park. Home-based errands include trips for health care, banking, or other household business. Home-based shopping trips include trips for both routine shopping and shopping for major purposes. Home-based social/culture trips include trips for recreation (except exercise), entertainment, visiting friends, and participation in civic and religious activities.

Figure 3. Distribution of walk trips and non-walk trips by trip purpose



Walk trips differ from non-walk trips in terms of both trip purpose and trip length. As Figure 3 shows, home-based work trips, home-based errands trips, and trips that do not begin or end at work or at home are underrepresented among walk trips. Work-based trips, home-based shopping trips, and home-based fitness trips are overrepresented among walk trips. This difference is most dramatic for home-based fitness trips. While only four percent of non-walking trips are home-based fitness trips, this category represents eighteen percent of all walk trips. With an average trip distance of a half-mile, walk trips are also substantially shorter than non-walk trips, which are just over six miles long, on average.

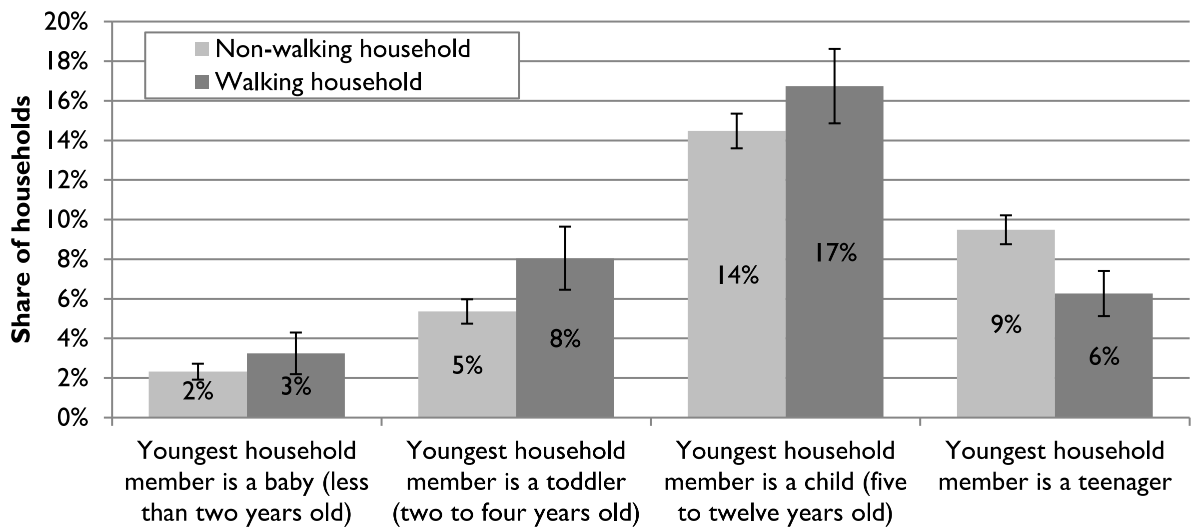
Figure 4. Differences in individual-level characteristics between walkers and non-walkers



In addition to these trip-level differences, the 2012 CHTS data also allow us to compare individual-level characteristics of people who made at least one survey-day walk trip (walkers) to those who traveled exclusively by other modes on the survey day (non-walkers). On average, walkers are slightly younger (by about eight months) than non-walkers, but this difference is not significant at a 95-percent confidence level (remember that our analysis does not include children). Figure 4 illustrates differences between walkers and non-walkers in terms of sex, driver's licensure, employment, disability, and nativity. Perhaps surprisingly, walkers are about as likely as non-walkers to have a disability. Walkers are more likely than non-walkers to be female, to be without a driver's license, not to be employed or looking for work, and to be foreign-born.

We also compare walking households (those in which at least one household member is a walker) to non-walking households. The average income of a walking household is about $78,000 per year. The average income of a non-walking household is higher at about $85,000 per year. However, the median incomes for both walking and non-walking households are equal: $61,000 per year. The average household size for both walking and non-walking household is also the same: 2.9 people. However, walking households have fewer vehicles per driver. Non-walking households have an average of one vehicle per driver, and walking households have an average of 0.8 vehicles per driver. Furthermore, although walking and non-walking households are, on average, the same size, the age profile of household members is different. As shown in Figure 5, the youngest person in a walking household is more likely to be a teen and less likely to be a toddler than the youngest person in a non-walking household.

Figure 5. Youngest household member by walking and non-walking households.



The confidential data from the 2012 CHTS includes the latitude and longitude coordinates for each trip end. Using these coordinates, we geocoded each trip origin to a census block group. This allows us to examine possible relationships between walking and the built environment. For data on the built environment, we turned to three different sources:

- Tract neighborhood types (Blumenberg et al., 2015; Voulgaris et al., forthcoming)
- Block group[5] Walk Score®[6]
- Block group nodal degree (Barrington-Leigh & Millard-Ball 2015)

Figure 6 draws on the neighborhood types developed in Blumenberg et al. (2015) and Voulgaris et al. (forthcoming) and shows the distribution of both walk trips and non-walk trips by neighborhood type in our four metropolitan regions. Walk trips are underrepresented in the three suburban neighborhood types (New Development, Patchwork, and Established Suburb), and overrepresented in Old Urban and Mixed Use (which we now label as "Job Center") neighborhoods. The percentage of total walk trips that originate in Old Urban neighborhoods is more than twice the share of total non-walk trips that originate in those neighborhoods.

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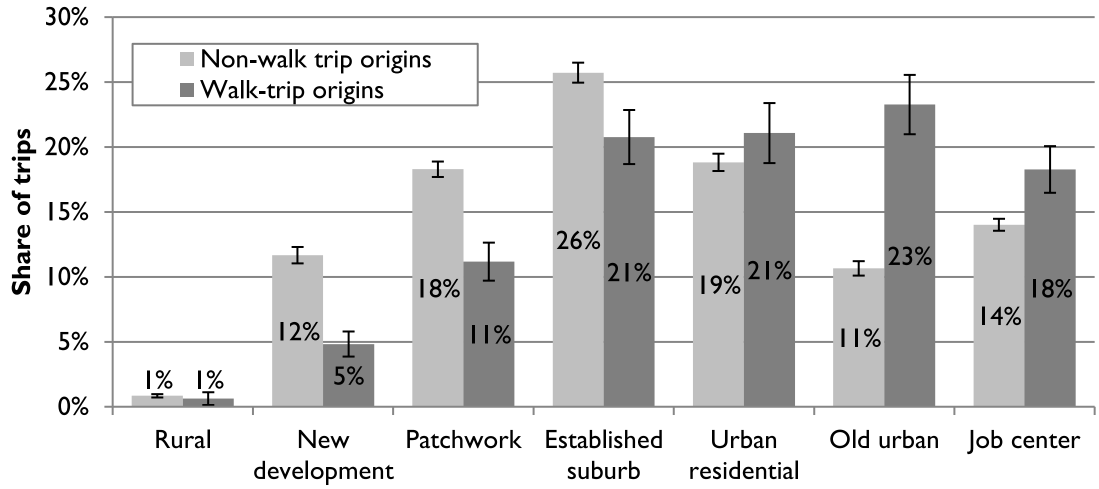
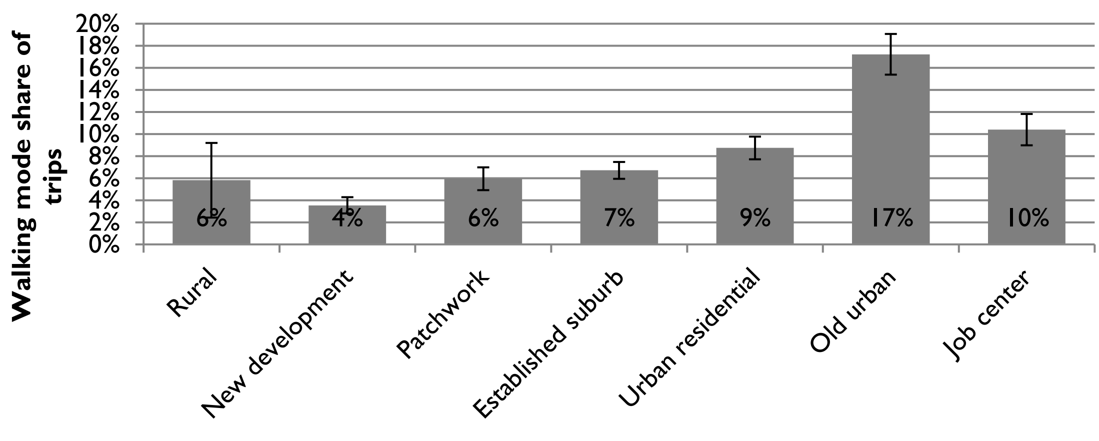
[5]Walk Score® is a point-based measurement. The score for each block group is based on the population-weighted center of that block group.
[6]Data were provided by Redfin Real Estate https://www.redfin.com

Figure 6. Distribution of walk trips and non-walk trips by neighborhood type



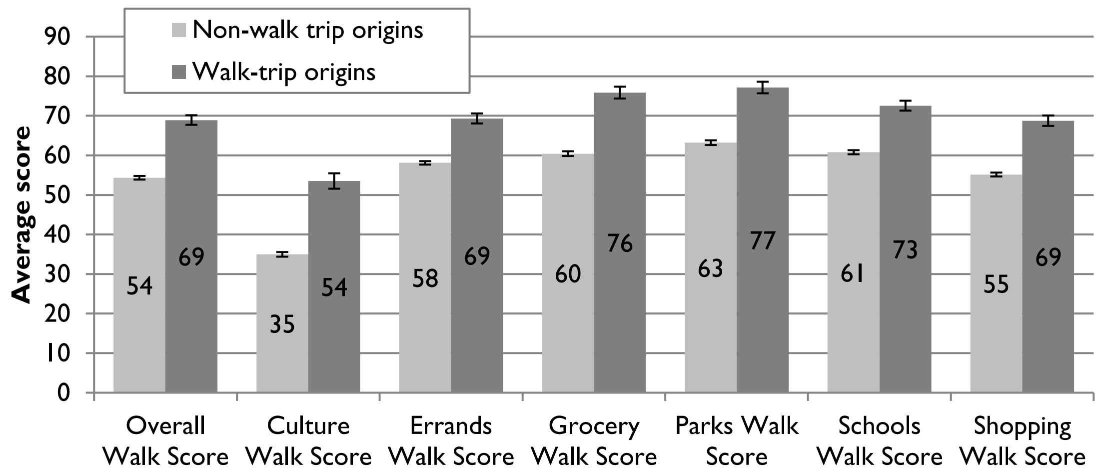
Another way to compare walking between neighborhood types is by the walking mode share within each type, as show in Figure 7. Again, Old Urban neighborhoods are unique. The walking mode share in Old Urban neighborhoods is seventy percent higher than that of Job Center neighborhoods, which have the next-highest walking mode share.

Figure 7. Walking mode share by neighborhood type



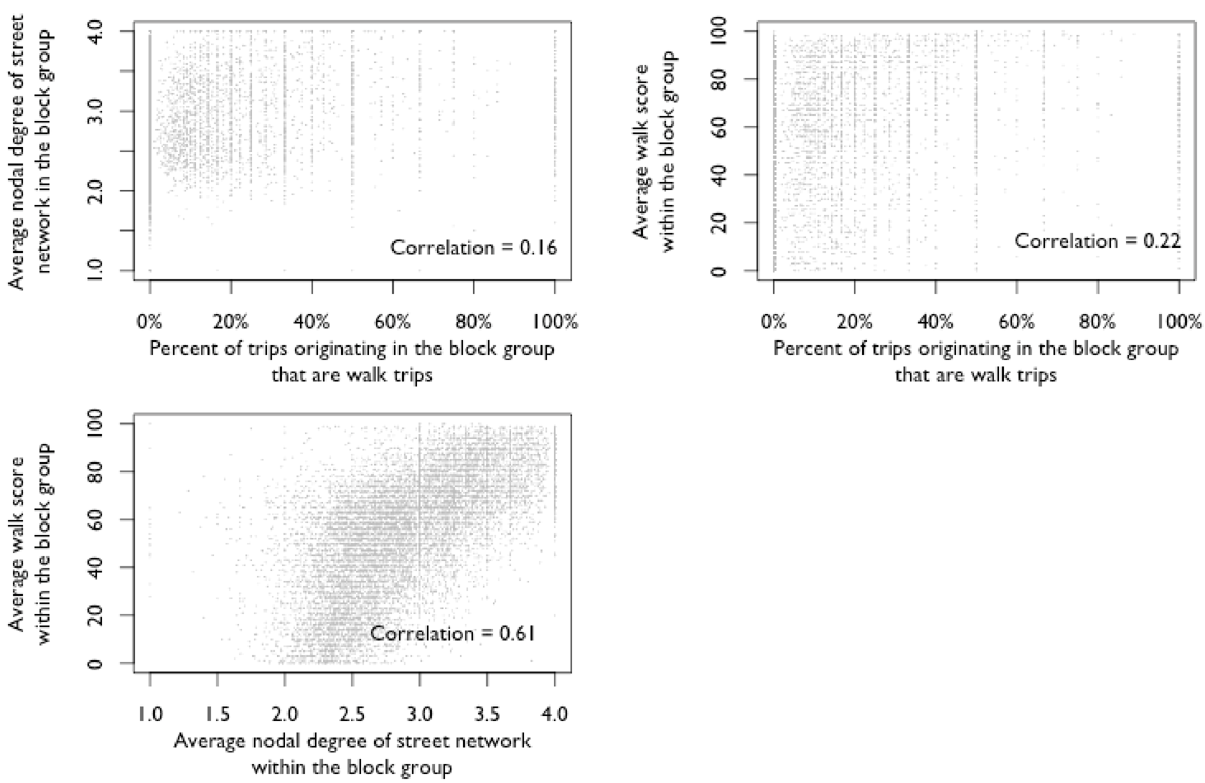
As Figure 8 shows, the average Walk Score® for the origin of a walk trip is about fifteen points higher than the average Walk Score® for the origin of a non-walk trip. This difference persists for each of the destination-type component Walk Scores® and varies from 11 points for the errands Walk Score® to 19 points for the culture Walk Score®.

Figure 8. Average Walk Score® for the origin block groups of walk trips and non-walk trips



The average nodal degree of the street network in a walk-trip origin block group is 3.1, which is higher than that of a non-walk-trip origin block group, which is 2.8. Although this difference is small, it is statistically significant at a 95-percent confidence level.

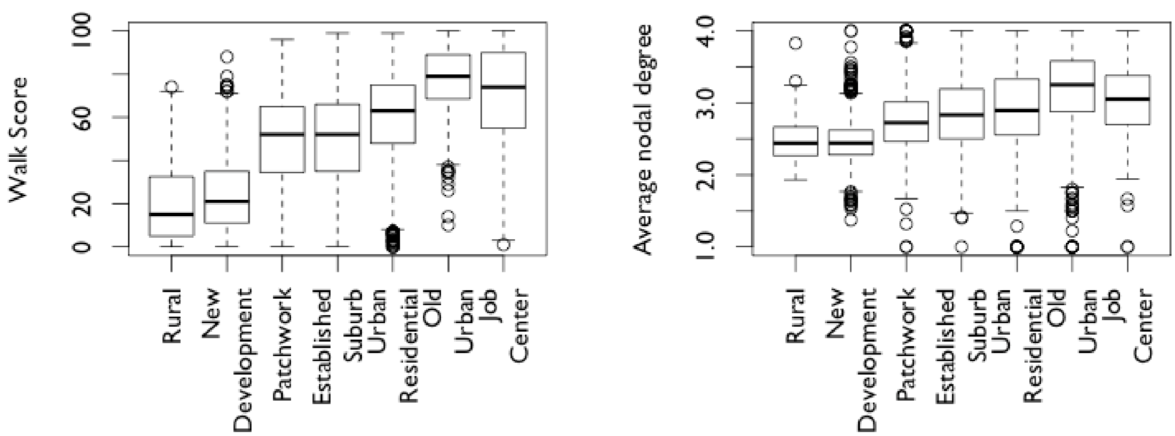
Figure 9. Relationship between a block group's Walk Score®, street network connectivity and walking mode share



As shown in Figure 9, there is a positive but weak relationship between a block group's Walk Score® and the walking mode share of trips that originate there, and also between the average street network nodal degree within a block group and the walking mode share of trips that originate there. Interestingly, Walk Score® and nodal degree are more highly correlated with one another than either measure is with the walking mode share within a block group.

Figure 10 presents box plots to illustrate how Walk Score® and average nodal degree vary by neighborhood type. Rural and New Development neighborhoods have the lowest Walk Scores® and average nodal degree; Old Urban and Job Center neighborhoods have the highest scores on both measures; and Patchwork, Established Suburb, and Urban Residential neighborhoods fall somewhere in the middle.

Figure 10. Box plots of variation in Walk Score® and street network connectivity by neighborhood type



Modeling methodology

To better determine the relationship between the built environment characteristics described above and walking in California's major metropolitan areas, we incorporated them into a logistic regression model predicting the likelihood that a particular trip will be a walk trip.

Several prior studies of walking behavior predict mode shares at the person or neighborhood level.[7] Others researchers have modeled mode choice at the trip level, and have found that trip-level characteristics such as trip length and purpose have important effects on mode

[7]See, for example, Cao et al. (2006), Forsyth et al. (2007), Forsyth et al. (2009), Joh et al. (2015) and Lee & Moudon (2006).

choice.[8] By specifying our model at the trip-level, we are able to control for these trip-level relationships in our analysis of the relationship between walking and the built environment

Person-level and neighborhood-level models typically analyze built-environment effects on mode share by estimating relationships between shares of walk trips and the built-environment characteristics of travelers' residential locations. However, many trips have origins or destinations that are outside the traveler's residential neighborhood. In fact, as shown in Figure 3, about thirty percent of all trips have both an origin and a destination that was not the traveler's home. By estimating a trip-level model, we are able to control for the built-environmental characteristics of trip origins, rather than only characteristics of the traveler's residential location.

Table 1 lists the variables that we include in our logistic regression model. We control for twelve trip, individual, and household characteristics in order to find the independent relationship between the likelihood of walking and each of three built environment variables. We estimate three models: the first predicts walking mode choice based only on the MSA where the traveler lives; the second adds the control variables from Table 1 which describes trip, individual, and household characteristics; and the third adds the variables describing the built environment. By comparing the model fit among these models, we can determine the overall effect of the built environment (as described by Walk Score®, neighborhood type, and street connectivity) on the odds of walking for a particular trip.

[8] See, for example, Cervero & Duncan (2003) and Kockleman (1997).

Table 1. Variables included in logistic regression model

Variable name	Description	Variable level	Variable type
Trip distance	Trip distance in miles	Trip	Control
Trip purpose	Categorical variable indicating one of the ten trip purposes shown in Figure 3, with home-based work as the omitted value.	Trip	Control
Age	Age of the respondent in years. Included as (age + age^2).	Person	Control
Sex	Categorical variable for the sex of the respondent, with male as the omitted value.	Person	Control
Driver's license	Categorical variable for whether the respondent is a licensed driver, with the lack of a driver's license as the omitted value.	Person	Control
Employment	Categorical variable indicating one of three employment categories: employed, unemployed (looking for work), and not in labor force (neither employed nor looking for work), with employed as the omitted value.	Person	Control
Disability	Categorical variable indicating whether the respondent is in one of three disability categories: No disability, mobility disability, or other disability, with no disability as the omitted value.	Person	Control
Nativity	Categorical variable indicating whether the respondent is native born or foreign born, with native-born as the omitted value.	Person	Control
Household size	The number of people in the respondent's household.	Household	Control
Vehicles per driver	The number of household vehicles per licensed driver	Household	Control
Income	Log-transformed annual household income	Household	Control
Youngest household member	Categorical variable indicating whether the youngest person in the household is in one of five age categories: Baby (younger than two years old), toddler (two to four years old), child (five to twelve years old), teenager (thirteen to 17 years old), or adult (older than 17 years old), with adult as the omitted value.	Household	Control
Metropolitan statistical area	Categorical variable for one of four metropolitan statistical areas: Los Angeles, the Bay Area, Sacramento, or San Diego, with Los Angeles as the omitted value.	Metropolitan statistical area	Geographic
Walk Score®	Overall Walk Score® in units of ten Walk Score® points	Census block group	Built environment
Neighborhood type	Categorical variable for one of the seven neighborhood types shown in Figure 6 with Established Suburb as the omitted value.	Census tract	Built environment
Average nodal degree	Average nodal degree of the street network	Census block group	Built environment

Model results

Table 2 compares the model fit for each of the three models in terms of the Akaike Information Criterion (AIC) and R^2 as well as the coefficients for the MSA indicator variables. The model explains about one percent of the variation in the decision to walk by MSA alone. When we include variables describing trip, individual, and household characteristics, the predictive power of the model increases significantly; this model explains 45 percent of the variation in the decision to walk. Adding the built environment variables provides an even better fit, but the difference is relatively minor; the full model explains an additional two percent of the variation in the decision to walk for a particular trip.

Table 2. MSA effects and logistic regression model fit

Model:	**MSA only**	**MSA plus control variables**	**Full model**
Model Fit			
AIC	52,848	26,513	25,943
R^2	0.01	0.45	0.47
MSA Effects (relative to Los Angeles), 95-percent confidence interval			
Bay Area	0.68 – 0.78	0.47 – 0.61	0.40 – 0.55
Sacramento	-0.35 – -0.15	-0.42 – -0.16	-0.24 – 0.02
San Diego	-0.23 – -0.04	-0.13 – 0.11	-0.02 – 0.23

By comparing the MSA effects from the three models, as shown in Table 2 and illustrated in Figure 11, we can determine the degree to which the control variables and the built environment variables each explain differences in walking mode shares among the four MSAs. The left set of bars in Figure 11 show that the odds that a trip will take place by walking are greater in the Bay Area and lower in Sacramento and San Diego than in Los Angeles (the odds that a trip will take place by walking is about the same in Sacramento as in San Diego). This is consistent with the mode shares shown in Figure 2. The middle set of bars shows that when we add controls for trip, individual, and household characteristics, the difference between Los Angeles and San Diego disappears, indicating that this difference can be primarily explained by non-built-environment characteristics. The right set of bars shows that when we add built environment characteristics, we have explained most of the difference between San Diego, Sacramento, and Los Angeles, although the odds of walking continue to be higher in the Bay Area for reasons that are not included in the model.

Figure 11. Effects of MSA on the odds of walking

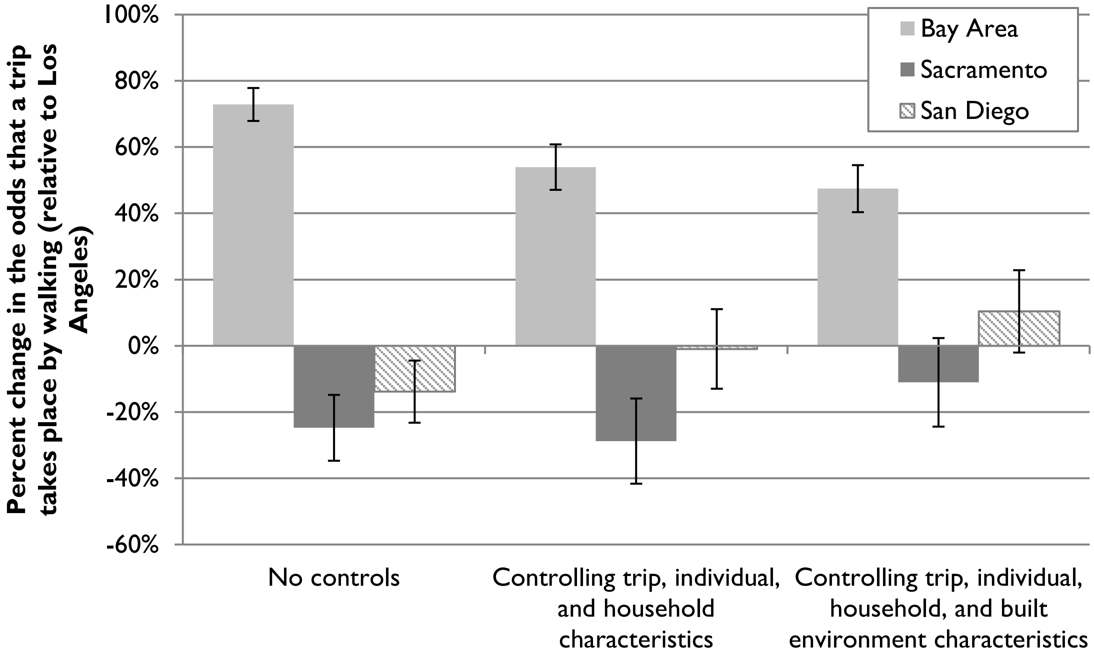


Table 3 shows the magnitudes of the relationship between the built environment variables and the decision to walk for a particular trip, based on the results of the full model. A ten-point increase in block-group's Walk Score® is associated with a nine percent increase in the odds that a trip originating there will take place by walking. A one-degree increase in the average nodal degree of the street network within a block group is associated with a 23 percent increase in the odds that a trip originating there will take place by walking.

Table 3. Relationships between built environment characteristics and the odds of walking

Built environment variable	Estimate	Standard error	95-percent confidence interval		
Walk Score® (in units of 10)	0.09	0.01	0.07	to	0.11
Average nodal degree	0.23	0.04	0.15	to	0.31
Neighborhood type (relative to Established Suburb)					
Rural	0.45	0.18	0.09	to	0.81
New Development	-0.03	0.08	-0.18	to	0.12
Patchwork	-0.07	0.05	-0.17	to	0.04
Urban Residential	-0.02	0.05	-0.12	to	0.08
Old Urban	0.21	0.06	0.10	to	0.32
Job Center	0.44	0.05	0.33	to	0.54

Note: Gray text indicates that the 95-percent confidence interval includes zero and the variable is not significant at a 95-percent confidence level

The difference in the odds of walking on a trip beginning in an Established Suburb neighborhood and a New Development, Patchwork, or Urban Residential neighborhood are not significantly different at a 95 percent confidence level. However, the odds that a trip will take place by walking is 21 percent greater if it begins in an Old Urban neighborhood and 44 percent greater if it begins in a Job Center neighborhood than if it begins in an Established Suburb neighborhood. The high densities and land use diversity within these neighborhood types might help explain these results. However, trips beginning in Rural neighborhoods are also 45 percent more likely than trips beginning in Established Suburb neighborhoods to take place by walking, when we control for Walk Score®, network connectivity, and trip, individual, and household characteristics. This is consistent with the observations in Figure 7 and Figure 10, which show that Rural neighborhoods have a moderate walking mode share in spite of having relatively low Walk Scores® and street network connectivity.

For comparison, Table 4 shows the estimated coefficients for the control variables in the full model.[9] Most of the control variables do have a significant relationship with the odds of walking, although the magnitudes of these relationships vary substantially. The relationship between trip distance and the odds that a trip will take place by walking is the most dramatic: a one-mile reduction in trip distance is associated with a 240 percent increase in the odds that the trip will take place by walking. A similar increase in the odds of walking are associated with a home-based fitness trip purpose (207 percent more likely to be a walk trip than a home-based work trip would be) or with the lack of a driver's license (177 percent more likely to be a walk trip than a trip by a person with a driver's license would be).

[9] For most control variables, the coefficient estimates in the model that excluded the built environment variables was within the 95-percent confidence interval of the coefficient estimates in the model that included them (shown in Table 4). Exceptions were for the non-home-based work trip purpose, household size, and number of vehicles per driver. The magnitudes of the coefficients for those three variables were greater when built environment variables were not included in the model.

Table 4. Relationships between control variables and the odds of walking

	Estimate	Standard error	95-percent confidence interval		
Trip characteristics					
Trip distance (miles)	-2.40	0.03	-2.47	To	-2.34
Trip purpose (relative to home-based work)					
Non-home-based work	0.26	0.09	0.09	To	0.42
Other non-home-based	-0.78	0.08	-0.93	To	-0.63
Home-based errands	-0.31	0.08	-0.46	To	-0.15
Home-based shopping	-0.05	0.08	-0.21	To	0.11
Home-based culture	0.31	0.09	0.14	To	0.48
Home-based dining	0.30	0.10	0.11	to	0.50
Home-based fitness	2.07	0.08	1.90	to	2.23
Home-based school	1.06	0.19	0.69	to	1.43
Home-based other	0.43	0.20	0.05	to	0.82
Individual characteristics					
Age	0.03	0.01	0.01	to	0.04
Age squared	-3.8×10^{-4}	6.5×10^{-5}	-5.0×10^{-4}	to	-2.5×10^{-4}
Sex (relative to male)					
Female	-0.05	0.03	-0.11	to	0.01
Driver's license (relative to unlicensed)					
Licensed	-1.77	0.06	-1.89	to	-1.64
Employment (relative to employed)					
Unemployed	0.14	0.08	-0.01	to	0.29
Not in labor force	0.17	0.04	0.09	to	0.25
Disability (relative to no disability)					
Mobility disability	-0.68	0.10	-0.88	to	-0.47
Other disability	-0.75	0.11	-0.96	to	-0.53
Nativity (relative to native-born)					
Foreign-born	0.10	0.04	0.02	to	0.18
Household characteristics					
Household size	-0.11	0.02	-0.15	to	-0.08
Vehicles per driver	-0.82	0.04	-0.90	to	-0.73
Income (log-transformed)	-0.01	0.02	-0.05	to	0.03
Youngest household member (relative to adult)					
Baby	0.28	0.11	0.08	to	0.49
Toddler	-0.01	0.08	-0.16	to	0.14
Child	-0.05	0.06	-0.16	to	0.06
Teen	-0.17	0.07	-0.31	to	-0.04

Note: Gray text indicates that the 95-percent confidence interval includes zero and the variable is not significant at a 95-percent confidence level

Discussion

Overall, trip, individual, and household characteristics explain more of the variation in the decision to walk than do characteristics of the built environment, as shown by the small increase in model fit that is achieved from adding the built environment variables to the control variables.

The differences in the odds of walking that can be explained by specific individual characteristics are also, for the most part greater than the differences explained by specific built environment characteristics. For example, the difference in the odds of walking associated with having a driver's license is four times the difference that would be expected based on a fifty-point difference in Walk Score®. The difference in the odds of walking for a trip beginning in an Established Suburb neighborhood (the most common neighborhood type in the study area) compared to those for a trip beginning in an Old Urban neighborhood (the neighborhood type with the most walking), would be about the same as the difference between a trip by an employed person and one by a person who is not in the labor force. A trip by a person with a disability in a block group with an average nodal degree of about four (a perfect grid network) as likely to be a walk trip as one by a person with no disability in a block group with an average nodal degree of about one (where all streets are dead ends).

In fact, holding all of the control variables constant, the greatest difference in the odds of walking that we would expect to observe based on varying all of the built environment variables from their minimum possible values to their maximum possible values would be a change of about 75 percent —the equivalent of reducing a trip's distance by about a third of a mile.

These findings are consistent with prior studies that suggest that socioeconomic factors have greater effects on mode choice than characteristics of the built environment (Ewing & Cervero 2010) and that dramatic changes in the built environment are required to achieve moderate changes in travel behavior. For example, a meta-analysis by Ewing and Cervero (2010) finds that a doubling in density (measured as population density, employment density, or commercial floor-area ration) is associated with increases in walking of about seven to four percent; a doubling of diversity and destination accessibility measures (an entropy index, job-housing balance, distance between homes and stores, or number of jobs within one mile) is associated with increases in walking of 15 to 25 percent.

Conclusion

Although the built environment has less of an effect on the decision to walk than trip, individual, and household characteristics, these effects are not unimportant for planners and policy makers who seek to increase utilitarian walking. In general, planners and policy makers can do little to influence the individual and household characteristics of travelers (and to the extent that they can, they probably should not). They do, however, have a variety of tools at their disposal to facilitate the development of built environments that are conducive to walking. The results of this study suggest that such tools can have modest but real effects on the choice to walk for a particular trip.

This study does not assess potential relationships between the built environment and trip characteristics other than mode. However, such relationships could offer planners and policy-makers an opportunity to indirectly influence walking mode choice by reducing trip distances, particularly to destinations that correspond with trip purposes that are associated with greater odds of walking, such as fitness, culture, school, and dining.

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III. The increase in walking: What role for the built environment?

Introduction

Data show that rates of walking have increased over time (Ham et al., 2005; Joh et al., 2015; Pucher et al., 2011; Simpson et al., 2003; Tudor-Locke et al., 2007; U.S. Department of Transportation, 2010). Using a variety of sources and measures, these studies document recent changes in walking in the U.S. Yet very few of these studies analyze the determinants of these changes, the focus of our work. In this analysis, therefore, we examine changes in walking in California. We draw on data from the 2001 and 2012 California Household Travel Surveys to determine whether there has been an increase in walking in the four major metropolitan regions in the state—the Bay Area, Los Angeles, Sacramento, and San Diego—where more than 60 percent of the state's population resides. We then use a set of logistic regressions to identify changes in the individual, household, trip, and built-environment characteristics that we predict explain the observed increase in walking across all four metropolitan regions.

We find that the change in walking has been due to a change in the composition of the population toward population groups more likely to be "walkers," those who take any trips by walking, as well as an increase in the effect of some characteristics on walking over time. With respect to the first, the changes include a substantial decline in the percentage of the population with driver's licenses, the percentage of the population who are employed, and the average number of vehicles per driver. Neighborhood characteristics have also shifted in ways that are conducive to walking. Three characteristics—trip length, the share of home-based fitness trips, and the share of the study population living in the Bay Area—not only changed in a direction consistent with increased walking, but the influence of these factors on walking also increased between 2001 and 2012, magnifying the effect of these changes.

This demonstrates that substantial changes in walking mode share are possible through the combination of a variety of factors, even when the effect of each individual factor may be small. It also suggests that the relationship between walking mode share and trip, household, and neighborhood characteristics can vary over time. This highlights to importance of frequent calibration and validation of models used to predict walking mode share for planning purposes.

Change in walking

Data from a variety of sources show an increase in walking rates over time in the U.S. (See Appendix A for a summary of these studies.) The National Household Travel Survey (NHTS), a national inventory of daily travel in the U.S., shows that the percentage of trips taken on foot increased from 8.6 percent in 2001 to 10.4 percent in 2009 (Santos et al., 2011). There was also a 28 percent increase in the number people accessing transit by walking from 2001 to 2009 (Freeland et al., 2013). Due to inconsistencies in collecting data on walk trips, identifying where this upward trend began is difficult (Clifton & Krizek, 2004). Traditional travel surveys tend to undercount short trips, many of which are taken on foot (Stopher & Greaves, 2007), and the NHTS only began specifically instructing survey respondents to report walk trips in 2001 (Santos et al., 2011). However, there is some evidence that walking mode shares in the United States have been increasing since as early as 1995. For example, in a study of short trips (one mile or less) Ham et al. (2005) find an increase in walking mode share between 1995 and 2001.

Walking rates have increased according to data from other studies, a finding that validates the trends from national travel surveys. For example, the Behavioral Risk Factor Surveillance System (BRFSS) is sponsored by a number of federal agencies including the Centers for Disease Control and Prevention, and is the nation's premier system of health-related telephone surveys. Data from the BRFSS show an increase in the prevalence of leisure walking from 1987-2000 (Simpson et al., 2003). Similarly, data from the American Heritage Time Use Study find an increase in the percentage of adults that walks for exercise from 2.9 percent in 1985 to 5.4 percent in 2003 (Tudor-Locke et al., 2007). The duration of time adults spent walking for exercise also increased from 30 to 45 minutes per day.

Increases in walking have not been uniform across population groups. Low-income adults, women, minorities, and working-age adults have experienced the largest increases in walking (Freeland et al., 2013; Pucher et al., 2011; Simpson et al., 2003). In contrast, rates of walking among seniors have lagged (Pucher et al., 2011). Data from the 2001 and 2009 NHTS show that the elderly (65 years and older) reported a decline across two measures – the percentage that walked per week (45 percent to 41 percent) and the percentage that took five or more walk trips per week (from 31 percent to 30 percent) (Pucher et al., 2011). Increases in walking also vary across cities. As might be expected, the percentage of workers that walk to work is highest in large, dense cities such as Boston (15 percent), Washington, DC (12 percent) and New York (10.3 percent) (McKenzie, 2014). However, among the largest 50 cities, only Atlanta, Boston, Chicago, Cleveland, Omaha, Sacramento, San Jose, and Seattle experienced statistically significant gains from 2000 to 2008-2012 in the percentage of people that walked to work (McKenzie, 2014).

Amidst these promising trends, these data suggest a few areas of concern. First, despite numerous planning efforts aimed at creating walkable, mixed-use communities, there has been a substantial decline in the percentage of commuters that walk to work. The walk commute share fell from 5.6 percent in 1980 to 2.8 percent in 2008-12 (McKenzie, 2014). This finding may or may not be troublesome since commute trips comprise only 16 percent of all trips (Santos et al., 2011). Second, perhaps more problematic is the fact that despite increases in walking, even people who are walking still are not active enough to meet national public health goals. Simpson et al. (2003) find no increase in the prevalence of people meeting the recommendation for moderate physical activity for at least 30 minutes per day, five or more days per week. Only 20 percent met this goal, a figure well below the 30 percent target.

What explains observed increases in walking? There is a large and growing body of research on the determinants of walking much of it focused on the relationship between the built environment and walking behavior.[10] Diverse in approach and data, these studies show that socio-demographic factors such as age, race/ethnicity, immigrant status, household structure, education, and income better predict walking behavior than attributes of the built environment. Although less influential, the built environment—measured by characteristics such as density, proximity to destinations, mixed-land use, and street connectivity—can also play a role. Walkable neighborhoods may motivate walking; conversely families wanting to travel on foot may move to neighborhoods where they can more easily walk to nearby destinations.

Very few studies have sought to explain increases in walking. There are a few exceptions. Joh et al. (2015) use travel survey data for the Southern California region to predict changes in walk trip share and rate from 2001 to 2009 across 46 Regional Statistical Areas, a geographic unit used by the regional planning agency for determining socioeconomic development. They find an association between increases in walking and increases in population, employment, and transit service densities. The small sample size limited the number of variables included in their analysis.

[10] See Badland and Schofield (2005), Saelens and Handy (2008), Ewing and Cervero (2010), McCormack and Shiell (2011) for reviews of this literature.

A number of other studies attempt to isolate the effects of various interventions on walking. Ogilvie et al. (2007) review 19 randomized controlled trials and 29 non-randomized controlled studies and find that:

> "Interventions tailored to people's needs, targeted at the most sedentary or at those most motivated to change, and delivered either at the level of the individual (brief advice, supported use of pedometers, telecommunications) or household (individualised marketing) or through groups, can encourage people to walk more, although the sustainability, generalisability, and clinical benefits of many of these approaches are uncertain."

The most successful of these interventions increased walking by up to 30-60 minutes a week on average, at least in the short term. A few studies examine the relationship between infrastructure investments and walking. These studies suggest that safety improvements and the provision of high-quality, traffic-free walking routes increased walking; the largest effects were among individuals without automobiles (Boarnet et al., 2005; Goodman et al., 2014). Additionally, studies of household travel behavior before and after the opening of light rail systems find associations between light rail use and physical activity through walking (Brown et al., 2015; MacDonald et al., 2010).

Data

The primary data source for this study is the California Household Travel Survey (CHTS), a survey conducted by the California Department of Transportation approximately every ten years. The CHTS collects travel data from households throughout California. Members of participating households completed travel diaries with detailed information about all trips and activities during a pre-assigned 24-hour period, where dates were assigned to ensure that data was collected for every day for a full year. Upon completing the travel diary, survey participants reported their travel through a computer-assisted telephone interview or by returning the travel diaries by mail.

We limited our analysis to adult survey respondents living in one of California's four major metropolitan areas: Los Angeles (Los Angeles and Orange Counties), the Bay Area (San Francisco, Marin, San Mateo, Contra Costa, and Alameda counties), Sacramento (Sacramento, Placer, El Dorado, and Yolo counties), and San Diego (San Diego county). Since the focus of our analysis is on intra-metropolitan travel, we also excluded from our analysis trips that were longer than 150 miles.

Table 5. Differences in sample sizes between survey years

Unweighted sample size	2001 Survey	2012 Survey	% change
Number of households	2,992	14,419	382%
Number of people	4,612	24,442	430%
Number of trips	20,248	93,918	364%

Our analysis relies on data from the 2001 and 2012 CHTSs. There were some important differences in the survey methodology between the two years. First, the survey sample size was much larger in 2012 than in 2001, as shown in

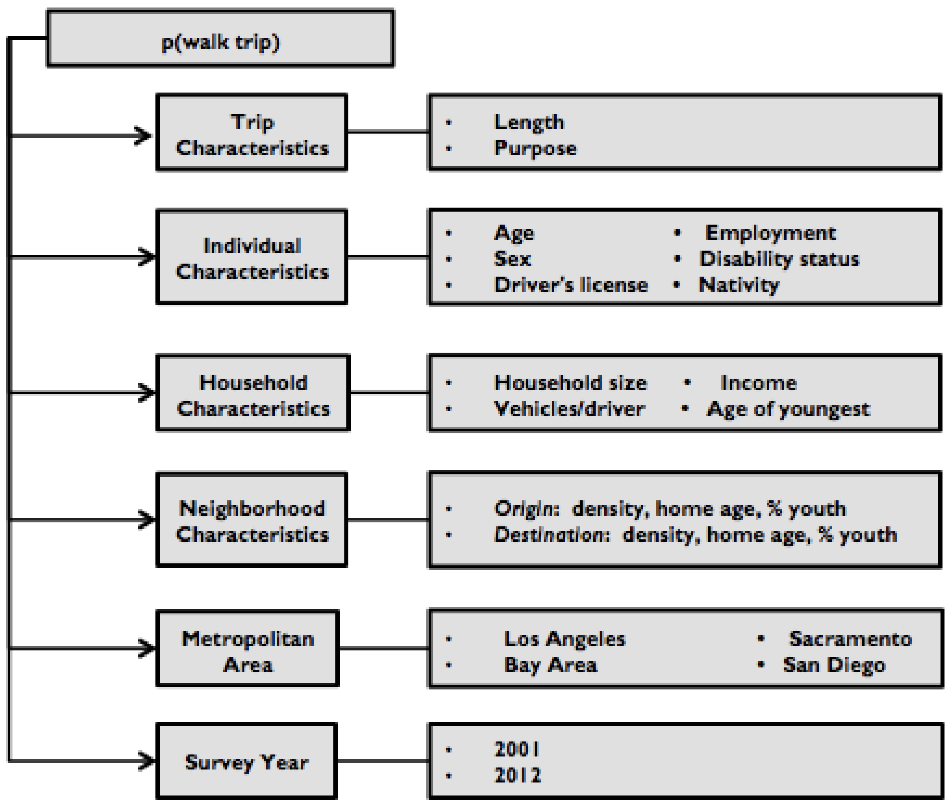
Table 5Table 11. Consequently, estimates of walking mode shares and other descriptive statistics for 2001 have more uncertainty and wider confidence intervals than the same statistics for 2012. Second, trips were defined differently between the two survey years. In 2001, a trip was defined as a change in location with the purpose of participating in non-travel activities. Thus, trips with a purpose of changing transportation modes (walking to a transit station or a remote parking location, for example) were generally not included, nor were loop trips (for instance, going on a walk for exercise, where the trip begins and ends in the same location). In 2012, both mode-changing trips and loop trips were counted as trips. In order to compare travel between the two years, we removed all loop trips from the 2012 data set and linked all mode-changing trips together to identify the trips' ultimate origins and destinations. Walk trips were defined as trips for which all segments took place by walking.

The confidential data from the CHTS includes the latitude and longitude coordinates for each trip end. Using these coordinates, we geocoded each trip origin and destination to a census block group. This procedure allows us to examine possible relationships between the likelihood of walking and characteristics of the neighborhoods in which a trip takes place. There are no longitudinal data sets characterizing the built environment in California over time. Therefore, for this analysis, we relied on data from the 2000 and 2010 decennial censuses to determine employment density, housing density, and the percentage of the population between the ages of 18 and 24 for each block group in which a trip from our sample began or ended.

Methodology

Based on our review of the existing literature on determinants of walking mode choice, we expect that the decision to walk is influenced by characteristics of the individual, the household, the trip, and the neighborhoods in which the trip takes place (both the trip origin and destination). We also anticipate that there may be additional differences in the likelihood of walking among the four metropolitan areas included in our study and between the two survey years. This conceptual model is illustrated in Figure 12.

Figure 12. Conceptual Model



We began our analysis by examining the change in the walking mode share between 2001 and 2012. We then examined changes in the walk mode share by metropolitan area, the change in walk trip distances, and changes in the individual and household characteristics of walkers relative to non-walkers.

Next, we determined how much each of the variables thought to influence walking mode shares have changed between 2001 and 2012. Then, in order to determine which of these changes might help to explain the observed increase in walking in California's major metropolitan areas, we incorporated them into a set of logistic regression models predicting the likelihood that a particular trip will be a walk trip.

Several prior studies of walking behavior predict mode shares at the person or neighborhood level.[11] Others researchers have modeled mode choice at the trip level, and have found that trip-level characteristics such as trip length and purpose have important effects on mode choice[12] By specifying our model at the trip-level, we are able to include these trip-level relationships in our analysis.

Person-level and neighborhood-level models typically analyze built-environment effects on mode share by estimating relationships between shares of walk trips and the built-environment characteristics of travelers' residential locations. However, many trips have origins or destinations that outside the traveler's residential neighborhood. In fact, as shown in Table 8, about twenty percent of all trips in 2012 and nearly 30 percent of trips in 2001 had both an origin and a destination that was not the traveler's home. By estimating a trip-level model, we are able to control for the built-environmental characteristics of trip origins and destinations, rather than only characteristics of the traveler's residential location.

For block-group density, we considered a model specification that included housing density and employment density as separate variables and another that combines the two into a single activity density variable indicating the number of jobs and homes per square kilometer. In all models, income and density variables were log-transformed, since the effect of these variables is more likely to be associated with proportional change (e.g. a ten percent increase) than with absolute change (e.g. 100 additional homes or jobs per square km, or $6,000 of additional income).

Since we excluded loop trips from the dataset, all trips have a distinct origin and destination. However, since many trips take place within a neighborhood, or between similar neighborhoods, the characteristics of trip origins and destinations are somewhat correlated, especially for walk trips, as Table 6 shows. Nevertheless, the correlation is not strong enough to preclude keeping both sets of neighborhood variables in the model if doing so provides the best model fit.

Table 6. Correlations between trip origin and destination characteristics

	All trips	Walk trips
Housing density	0.461	0.666
Employment density	0.340	0.754
Activity density	0.380	0.785
Housing age	0.428	0.672
Percent youth	0.228	0.713

[11]See for example, Forsyth et al. (2009), Joh et al. (2015), Rodrıguez & Joo (2004), Weinberger & Sweet (2012).
[12]See, for example, Cervero & Duncan (2003), Kockleman (1997) and Manaugh & El-Geneidy (2013).

Table 7 compares the fit of six different sets of variables characterizing neighborhood densities. Of these, the best-fitting model, as indicated by the lowest Akaike Information Criterion (AIC) score is one that that combines housing and employment density into a single activity density variable and includes information about both trip origins and destinations. Using this neighborhood specification and the other variables listed from the conceptual model in Figure 12, we ran three logistic regression models: one including all observations from both years, a second including only data from 2001, and a third including only data from 2012.

Table 7. Akaike Information Criterion (AIC) scores comparing model fit by neighborhood variables

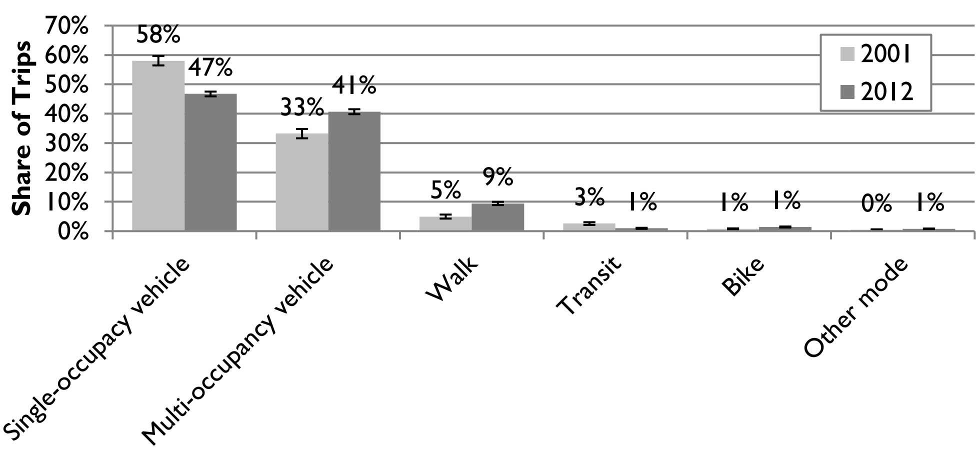
AIC score	Housing and employment density combined into a single activity density variable	Housing and employment density as separate variables
Origins only	31,854	32,000
Destinations only	31,877	32,028
Origins and destinations	31,720	31,878

By comparing coefficient estimates between the 2001 and 2012 models, we identified variables whose effect on walking mode choice varied by year. Based on these differences, we estimated a fourth model in which we include data from both years, with interaction terms to determine the change in effect size for those variables between 2001 and 2012.

Descriptive analysis

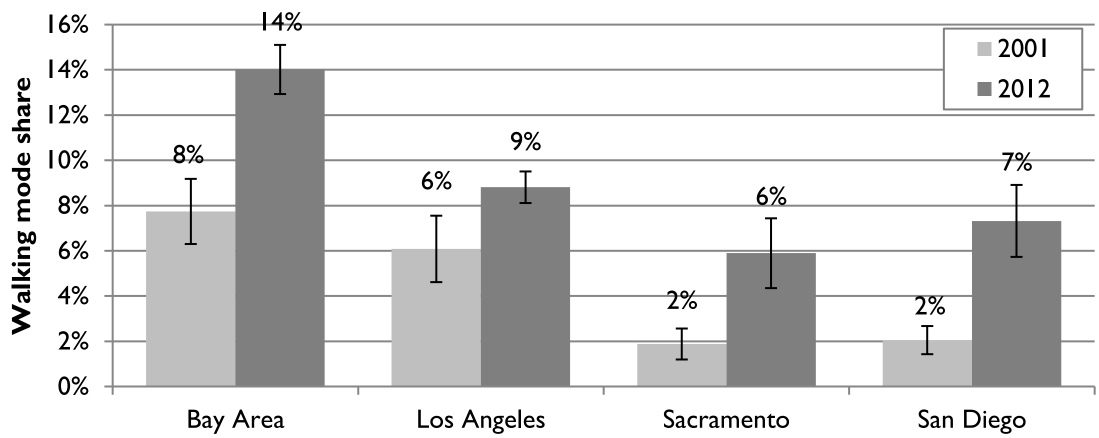
Figure 13 shows how mode shares have changed within the study area between 2001 and 2012. The greatest change was a reduction in the share of trips by single-occupancy vehicle from 58 percent in 2001 to 47 percent in 2012. This difference is offset by an increase in multi-occupancy vehicle trips from 33 to 41 percent (a 24 percent increase) and an increase in walking trips from five to nine percent (an 80 percent increase).

Figure 13. Changes in mode shares within the study area, 2001-2012



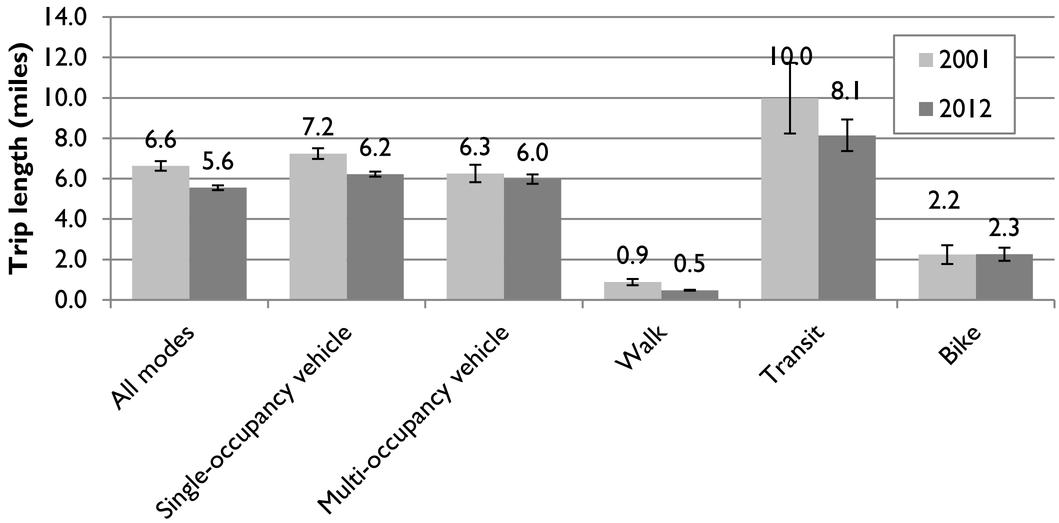
As Figure 14 shows, the increase in walking mode share varied by metropolitan area. The most modest gains were observed in the Los Angeles area, where the walking mode share increased by about fifty percent. The Bay Area, which began with the highest walking mode share, saw an increase of about 75 percent. Walking mode shares in both years were the lowest in the Sacramento and San Diego areas. However, these areas saw the most dramatic increase in walking; in both areas, the walking mode share increased about three-fold.

Figure 14. Increases in walking mode share by metropolitan area, 2001-2012



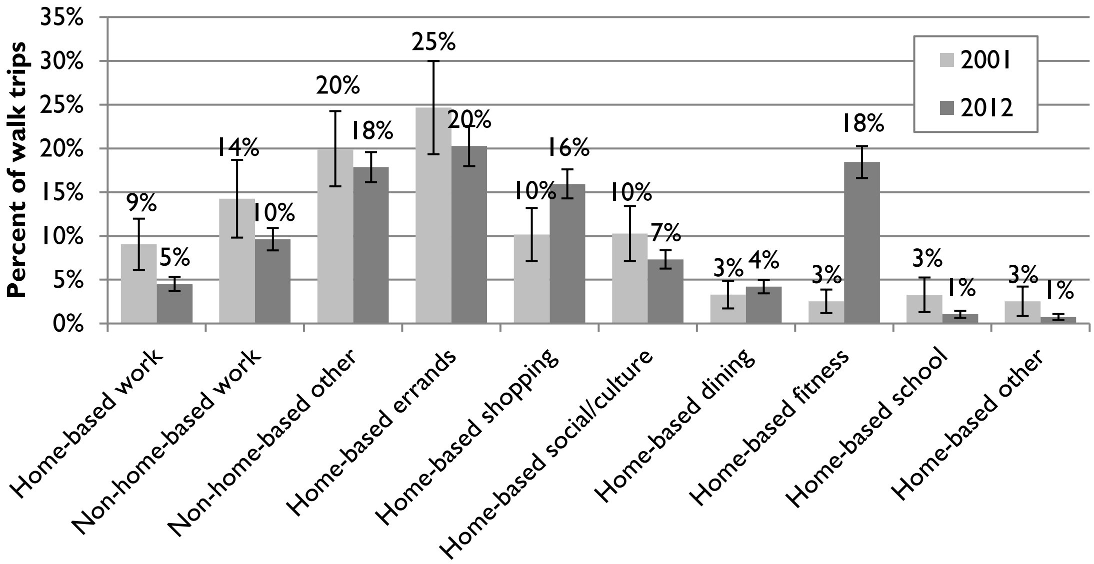
With the increases in walking mode share, we also observe changes in walk trip characteristics. As shown in Figure 15, trip distance decreased for all modes between 2001 and 2012. The average length of a walk trip declined from just under a mile in 2001 to half a mile in 2012. This may indicate that short walk trips have become more common, or that the survey instrument has improved to capture more short trips that had gone unreported in previous years.

Figure 15. Changes in trip distance by mode and year, 2001-2012



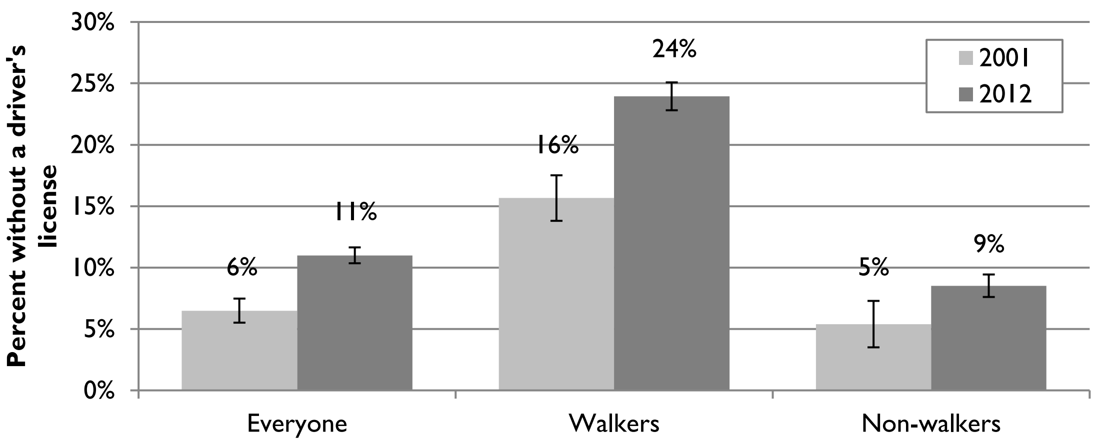
We defined ten different trip purpose categories, based on activities at trip origins and destinations. For the most part, these categories are self-explanatory. Home-based fitness trips are not loop trips (such as recreational walks or bike rides that begin and end at home), but rather trips to a location for fitness activities, such as a gym, a fitness class, or a park. Home-based errands included trips for health care, banking, or other household business. Home-based shopping trips included trips for both routine shopping and shopping for major purposes. Home-based social/culture trips included trips for recreation (except exercise), entertainment, visiting friends, and participation in civic and religious activities. Figure 16 shows the distribution of walk trips across these trip purposes in each survey year. The purposes of walk trips were fairly consistent between the two years, with the striking exception of home-based fitness trips, which increased from about three percent of all walk trips in 2001 to nearly a fifth of all walk trips in 2012.

Figure 16. Distribution of walk trips among trip purposes, 2001-2012



One explanation for the increase in walking may lie in reduced rates of driver's licensure. As Figure 17 shows, the share of the population without a driver's increased from six percent 2001 to 11 percent in 2012. This increase was especially pronounced among those who made at least one walking trip on the survey day ("walkers").

Figure 17. Changes driver's license status among walkers and non-walkers, 2001-2012



As shown in Figure 18, there were also large changes in employment status between 2001 and 2012, particularly in terms of the share of the population who were not in the workforce (meaning they were neither employed nor looking for work. As with driver's license status, this difference was more pronounced for walkers than for non-walkers.

Figure 18. Changes in employment status among walkers and non-walkers, 2001-2012

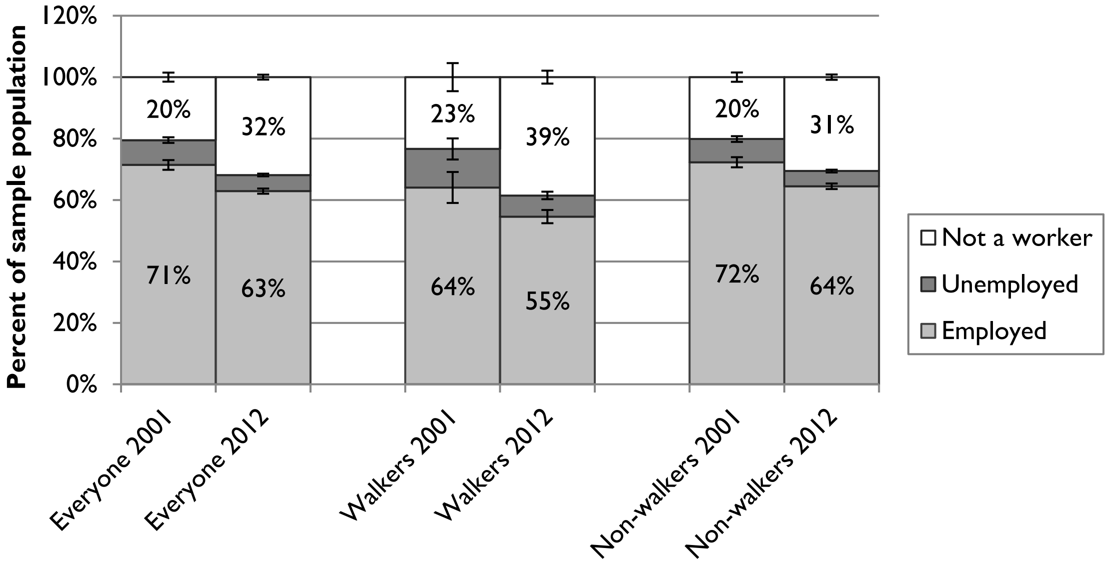


Figure 19 illustrates how household vehicle availability declined between 2001 and 2012. The average number of household vehicles per driver declined in the households of both walkers and non-walkers. In walker's households, vehicle availability had declined to less than one vehicle per licensed driver in 2012.

Figure 19. Changes in vehicle availability among walkers and non-walkers, 2001-2012

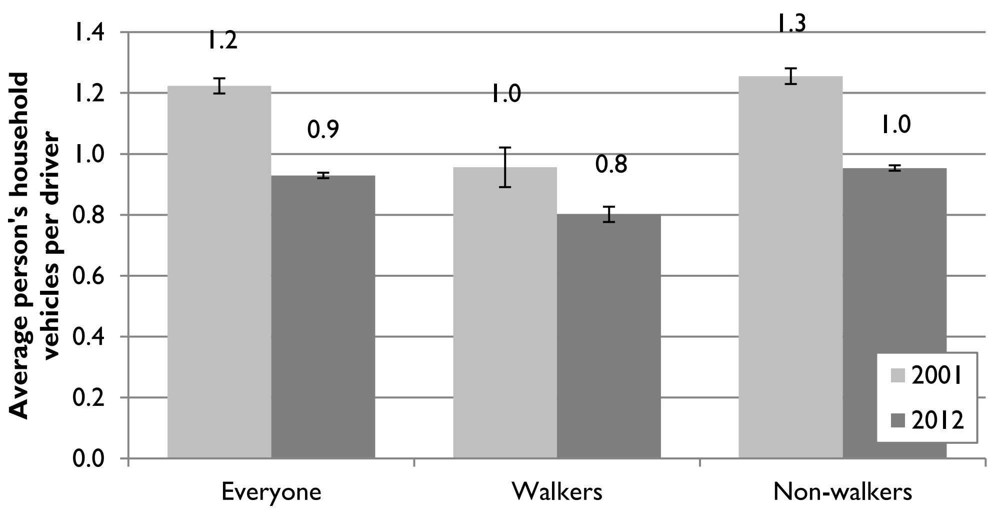


Table 8 shows other observed changes between 2001 and 2012, based on a combination of survey data and census data. Of particular interest for this study is the increase in the share of trips that take place by walking, which has nearly doubled from about five percent in 2001 to about nine percent in 2012. Compared to some of the changes highlighted in the figures above, the changes in housing and employment densities within the study area were relatively modest, as were the changes in the relative shares of the study area population living in each of the four metropolitan areas.

Table 8. Observed changes between survey sample years

	2001	2012	% change
Trip-level variables			
Percent walk trips[1]	5%	9%	80%
Average trip length (miles)[1]	6.6	5.6	-15%
Trip purpose[1]			
Percent home-based work	18%	12%	-33%
Percent non-home-based work	10%	7%	-30%
Percent non-home-based other	23%	23%	0%
Percent home-based errands	20%	24%	20%
Percent home-based shopping	11%	12%	9%
Percent home-based social/culture	7%	9%	29%
Percent home-based dining	4%	5%	25%
Percent home-based fitness	2%	6%	200%
Percent home-based school	2%	1%	-50%
Percent home-based other	3%	1%	-67%
Individual characteristics			
Average age[1]	47	47	0%
Percent female[1]	49%	53%	8%
Percent with no driver's license[1]	6%	9%	50%
Percent employed[1]	71%	63%	-11%
Percent not in labor force[1]	20%	32%	60%
Percent with a mobility disability[1]	2%	3%	50%
Percent with another disability[1]	2%	3%	50%
Percent foreign-born[1]	17%	28%	65%
Household			
Household size (Number of people)[1]	2.8	2.7	-4%
Vehicles per driver[1]	1.3	0.9	-31%
Median income (2012 dollars)[2]	$63,882	$64,170	0%
Percent with no children under 13[1]	79%	68%	-14%
Block-group			
Average housing density (homes per sq-km)[3]	1,572	1,696	8%
Average employment density (jobs per sq-km)[3]	1,281	1,299	1%
Average activity density (homes and jobs per sq-km)[3]	2,853	2,995	5%
Average home age (years)[3]	38	46	21%
Average percent youth (age 18-24)[3]	9%	10%	11%
Metropolitan Area			
Percent living in Los Angeles Area[3]	59%	57%	-3%
Percent living in Bay Area[3]	20%	19%	-5%
Percent living in Sacramento Area[3]	9%	10%	11%
Percent living San Diego Area[3]	13%	14%	8%

Notes:
1. Based on weighted 2001/2012 survey data
2. Median of block-group medians, based on weighted 2001/2012 survey data
3. Based on 2000/2010 census data

Model results

As described in the Methodology section, we initially estimated separate logistic regression models for each survey year. Detailed model results for these models are included in Appendix B. In each of the models that include data from a single year (2001 or 2012), the only statistically significant differences in coefficient estimates were for the following variables:

- trip distance,
- trip purpose,
- household size,
- age of the youngest household member, and
- metropolitan area

In order to capture these differences in one model with data from both years, we added interaction terms for survey year and each of the five variables listed above. The AIC score for this final model was 31,236, which indicates a better model fit than in the model with no interaction terms.

Detailed model results for the best-fit model are shown in Table 9. The first column shows the 95-percent confidence intervals for the estimated effects for each variable. For the variables that were interacted with the year indicator, this estimate should be interpreted to apply to observations from 2001. Otherwise, it applies to observations for both years. The second column shows the 95-percent confidence intervals for the estimated effects for the interactions with the year variable. This represents the difference between the observed effect in 2001 and the observed effect in 2012. The third column shows the 95-percent confidence interval for the marginal effects, which are computed as the estimated effect plus the interaction effect and can be interpreted to represent the effect in 2012. Confidence intervals for the marginal effects are calculated as 1.96 times the standard error, where the standard error is given by the following equation, where b_{eff} is the estimated effect and b_{int} is the interaction effect.

$$\sqrt{var(b_{eff}) + var(b_{int}) + 2cov(b_{eff}, b_{int})}$$

Table 9. Logistic regression predicting the odds that a trip will be a walk trip

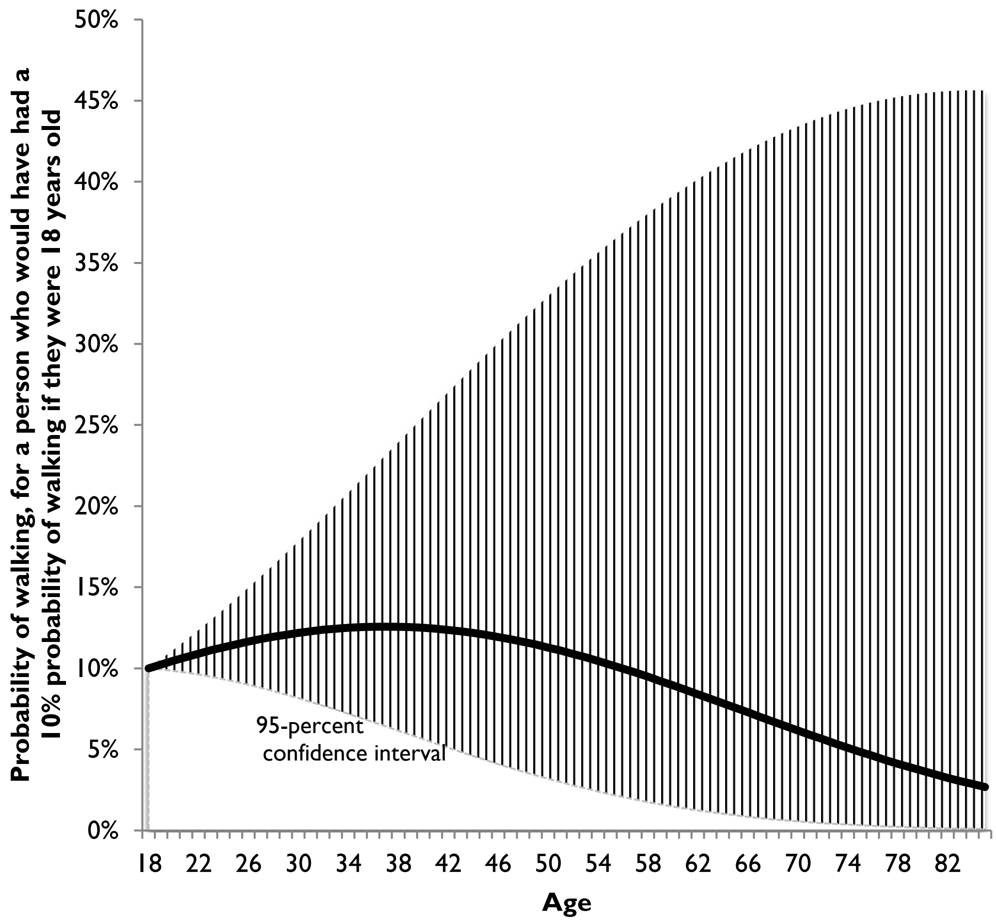
Variables	95-percent confidence intervals for coefficient estimates: Estimated effect			2012 Interaction effect			2012 Marginal effect		
Trip									
Trip length (miles)	-1.16	-	-0.97	-1.39	-	-1.16	-2.40	-	-2.27
Trip purpose (base: Home-based work)									
Non-home-based work	-0.20	-	0.48	-0.35	-	0.40	> -0.01	-	0.33
Non-home-based other	-1.07	-	-0.44	-0.37	-	0.32	-0.93	-	-0.63
Home-based errands	-0.53	-	0.10	-0.41	-	0.29	-0.43	-	-0.13
Home-based shopping	-0.97	-	-0.25	0.19	-	0.97	-0.19	-	0.12
Home-based social/culture	0.23	-	0.96	-0.66	-	0.14	0.17	-	0.51
Home-based dining	-1.05	-	-0.07	0.33	-	1.38	0.11	-	0.49
Home-based fitness	0.10	-	1.08	1.02	-	2.05	1.96	-	2.29
Home-based school	-0.48	-	0.68	0.16	-	1.52	0.58	-	1.30
Home-based other	-0.35	-	0.74	-0.39	-	0.94	0.08	-	0.85
Individual characteristics									
Age	0.01	-	0.03						
Age squared	$-4x10^{-4}$	-	$-2x10^{-4}$						
Female (base: Male)	-0.10	-	0.01						
Driver's license (base: Unlicensed)	-1.80	-	-1.58						
Employment (base: Employed)									
Looking for work	0.11	-	0.26						
Not a worker	0.06	-	0.32						
Disability status (base: No disability)									
Mobility disability	-0.79	-	-0.42						
Other disability	-0.82	-	-0.44						
Foreign-born (base: Native-born)	-0.01	-	0.14						
Household									
Household size (people)	-0.36	-	-0.17	0.06	-	0.26	-0.13	-	-0.07
Vehicles per driver	-0.79	-	-0.64						
Income (log)	-0.05	-	0.02						
Youngest person (base: Adult)									
Baby	0.90	-	1.89	-1.62	-	-0.55	0.11	-	0.52
Toddler	0.47	-	1.22	-1.25	-	-0.45	-0.16	-	0.14
Child	0.21	-	0.78	-0.81	-	-0.21	-0.12	-	0.10
Teen	-0.92	-	0.06	-0.26	-	0.75	-0.32	-	-0.06
Trip destination block-group									
Activity density (log)	0.15	-	0.23						
Average home age (decades)	< 0.01	-	0.04						
Percent youth (age 18-24)	0.28	-	0.91						
Trip origin block-group									
Activity density (log)	0.16	-	0.23						
Average home age (decades)	0.03	-	0.07						
Percent youth (age 18-24)	0.45	-	1.07						
Metropolitan Area									
Base: Los Angeles									
Bay Area	0.02	-	0.40	0.05	-	0.45	0.40	-	0.53
Sacramento	-0.95	-	-0.39	0.42	-	1.03	-0.07	-	0.18
San Diego	-0.81	-	-0.31	0.47	-	1.03	0.07	-	0.31
Year									
2012 (base: 2001)	0.21	-	1.01						

Note: Gray text indicates that the 95-percent confidence interval includes zero, so the coefficient is not significant at a 95-percent confidence level.

All of the individual characteristics and block-group characteristics had the same relationship with the likelihood of walking in both survey years, as did two household characteristics: household income and the number of household vehicles per driver.

As shown Table 9 and illustrated in Figure 20, the traveler's age has a modest, but statistically significant effect on the likelihood that a trip will be made by walking. Holding other variables constant, for a person with a ten-percent probability of making a walk trip, the probability of walking increases slightly until peaking at 13 percent in the traveler's mid-thirties, then steadily decreases to less than three percent by the traveler's mid-eighties.

Figure 20. Effect of age on the probability of walking



Neither sex nor nativity has a statistically significant effect on the odds that a trip will be a walk trip. As shown in Figure 21, driver's licensure, employment, disability, and household vehicle availability all have statistically significant relationships with the odds that a trip will be a walk trip.

For people who are not employed, either because they are not in the work force or because they have not found employment, the odds of a given trip being a walk trip are about twenty percent higher than for people who are employed.

Disability (whether mobility or other disability) reduces the odds that a trip will take place by walking, and the magnitude of this effect is about the same as that of adding an additional household vehicle per driver. Having a driver's license likewise reduces the odds of walking, and the magnitude of this effect is about twice that of having a disability or adding an additional vehicle per driver.

Figure 21. Effects of licensure, employment, disability, and vehicle availability on the odds of walking

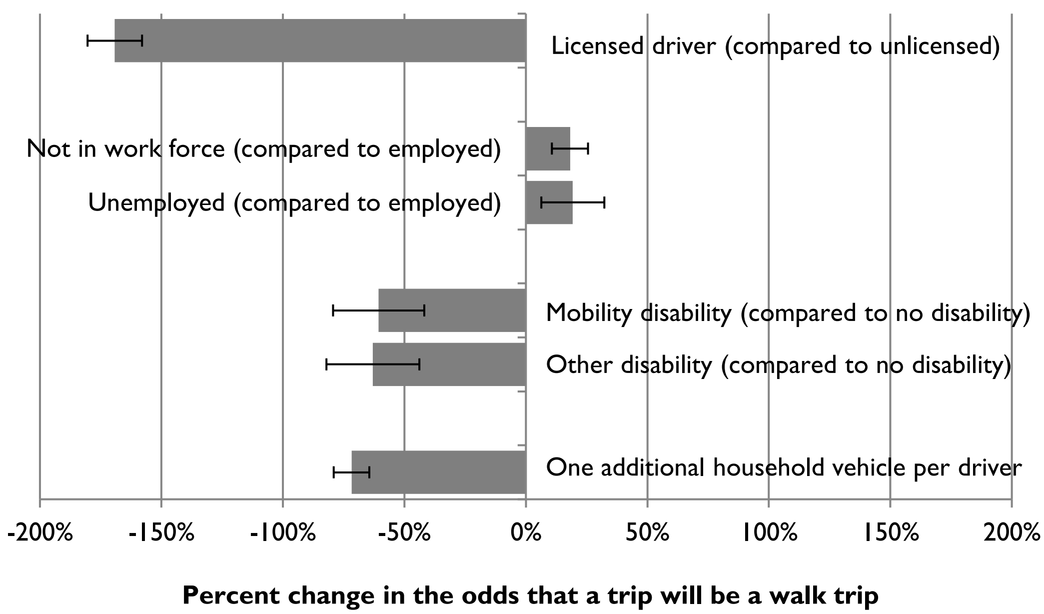
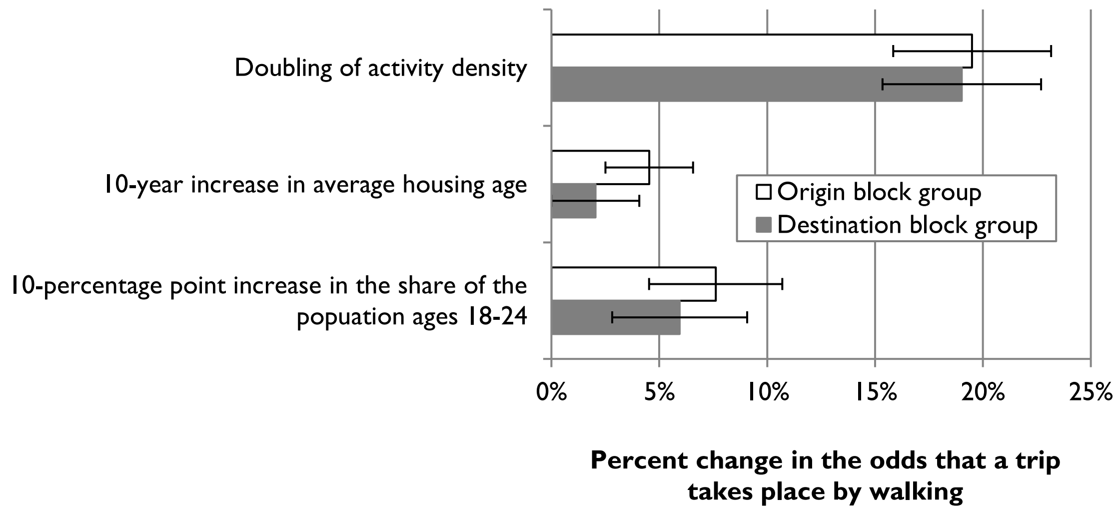


Figure 22 illustrates the effects of three block-group characteristics at the trip origin and destination on the odds that a trip will be a walk trip. For the most part, the effects are modest. Doubling the activity density at either the trip origin or trip destination is associated with an increase of just under twenty percent in the odds of walking. This would be about the same as the effect of increasing the average block-group housing age by over 40 years or increasing the share of young people by about 25 percentage points.

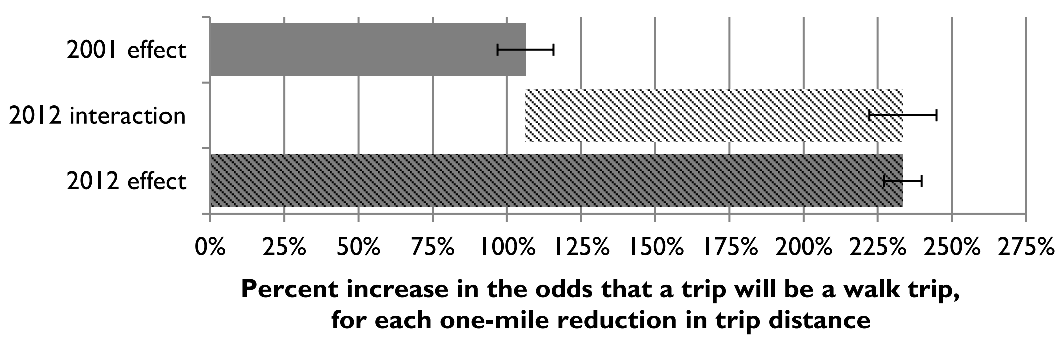
Figure 22. Effects of block-group characteristics on the odds of walking



The effects of trip characteristics and household structure (household size and the age of the youngest household member) on the likelihood of walking changed between the two survey years.

Figure 23 illustrates the effect of trip distance on the odds that a trip will be a walk trip and the degree to which this effect has changed between 2001 and 2012. In 2001, the odds of walking would approximately double for each one-mile reduction in trip distance. By 2012, it appears that Californians had become even more sensitive to trip distance, such that the odds of a walking would more than triple with a one-mile reduction in trip distance.

Figure 23. Changes in the relationship between trip distance and the odds of walking, 2001-2012



The effect of trip purpose on the likelihood of walking also changed. Of the nine trip purposes included in the model, five have interaction term coefficients that are not significant at a 95-percent confidence level, indicating that the effects of these trip purposes relative to home-based work trips was about the same in 2012 as in 2001. In general, for both years, non-home-based work trips, home-based errand trips, and home-based other trips were as likely to be walk trips as home-based work trips were. Non-home-based other trips were less likely to be walk trips than home-based work trips were, and home-based social/cultural trips were more likely.

Figure 24 illustrates the changes in the effect of trip purpose on walking between 2001 and 2012 for the trip purposes where these changes were significant. In 2001, home-based shopping trips were less likely than home-based work trips to be walk trips. By 2012, this effect seems to have disappeared, so that home-based shopping trips are about as likely as home-based work trips are to be walk trips.

For home-based dining trips, the change in the effect between 2001 and 2012 was even more dramatic: enough to change the direction of the effect relative to home-based work trips. While home-based dining trips were less likely than work trips to be walk trips in 2001, they were more likely than home-based work trips to be walk trips in 2012.

In 2001, the odds of a trip being a walk trip were just over fifty percent higher for home-based fitness trips than for home-based work trip. By 2012, this already large effect had grown so that the odds of walking for a home-based fitness trip were more than triple those for a home-based work trip.

Finally, in 2001, home-based school trips were no more likely to be walk trips than home-based work trips were. However, by 2012, the odds of walking for a home-based school trip were almost double those for a home-based work trip.

Figure 24. Effects of trip purpose on the odds of walking

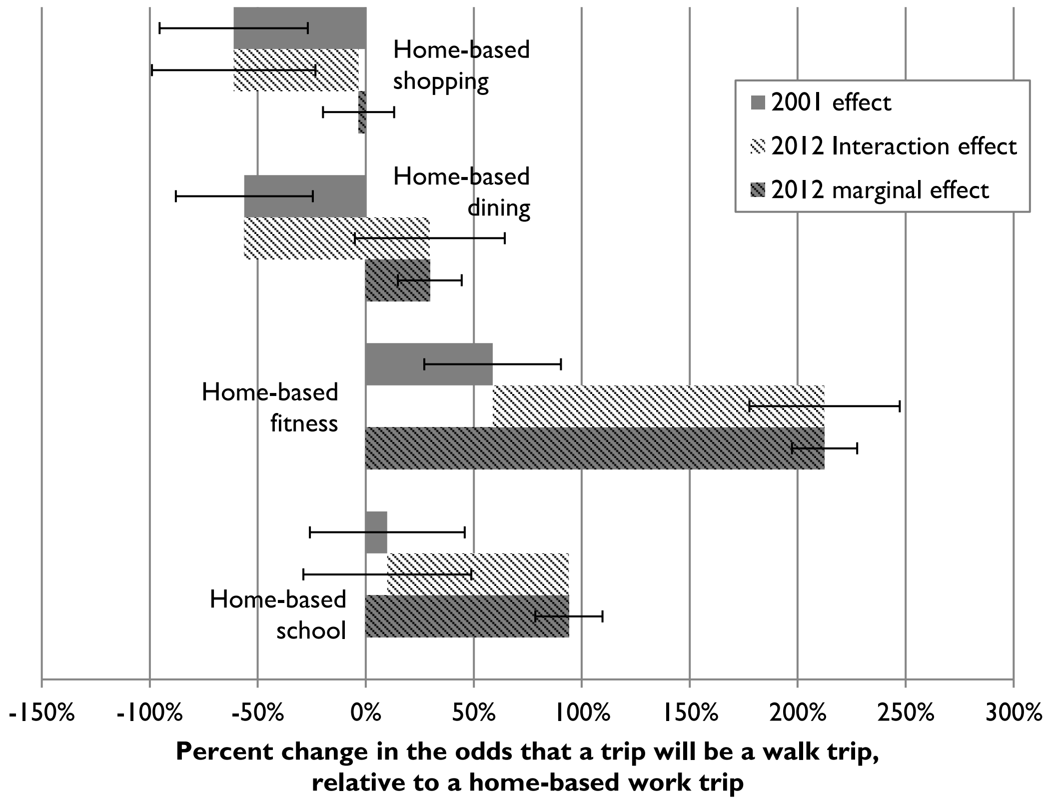
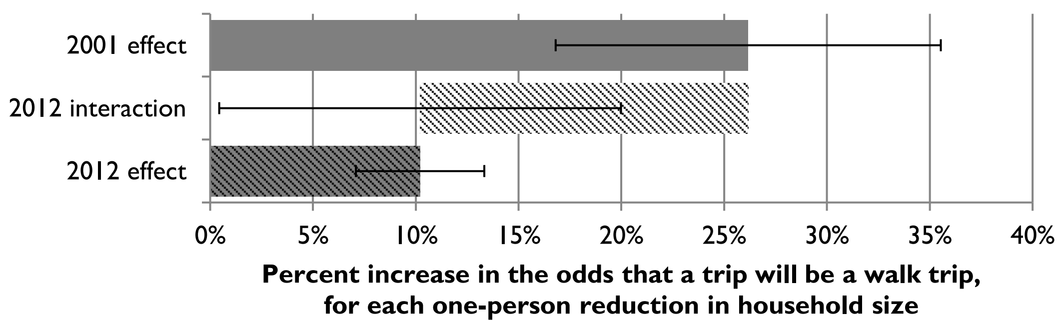


Figure 25. Effect of household size on the odds of walking



As Figure 25 shows, larger households are associated with increased odds that a trip by a household member will be a walk trip, although the magnitude of the effect is much smaller in 2012 than in 2001. In addition to the number of household members, the ages of household members also relates to the likelihood that a trip will take place by walking. Figure 26 illustrates the effect of household children on the odds that a trip will be a walk trip. In general, children make it more likely that a trip will be a walk trip. In 2001, the greatest effect is observed for the presence of a baby, and the second-greatest effect is for the presence of a toddler. This pattern continues in 2012, but all effects are diminished so that only the effect of the presence of a baby is associated with a significant increase in the odds that a trip will be a walk trip. The presence of teenagers in a household does not have a significant effect on the odds of walking on a given trip in 2001, but by 2012, household teenagers were associated with reduced odds of walking.

Figure 26. Effect of the presence of children on the odds of walking

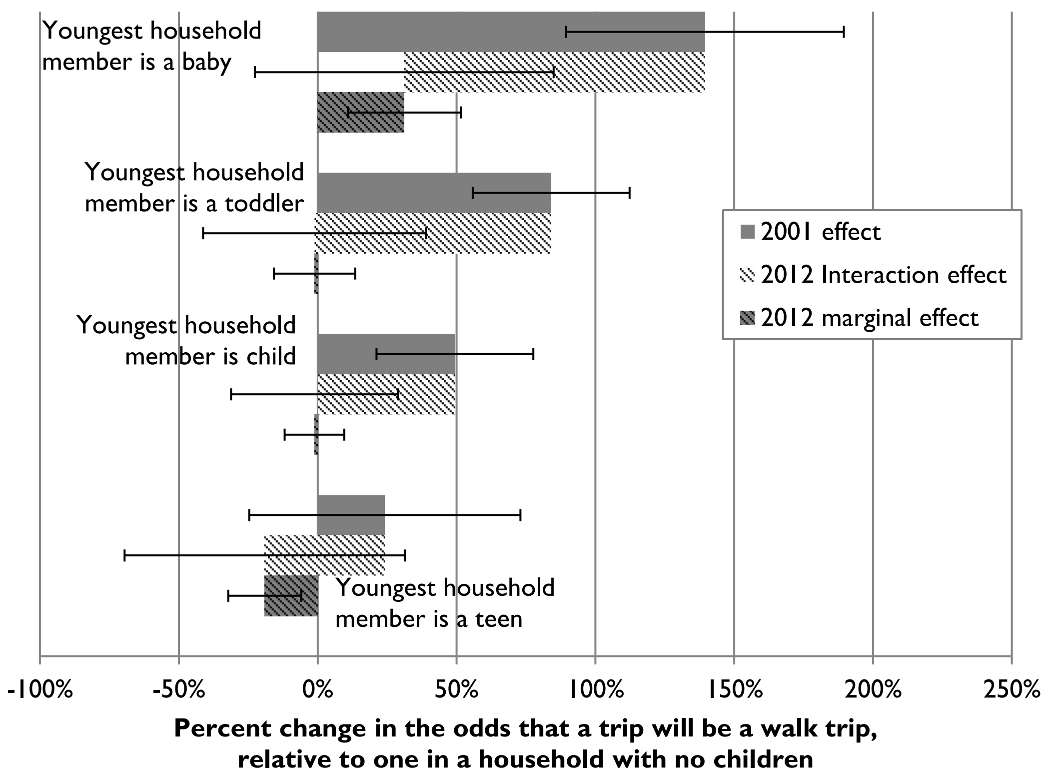
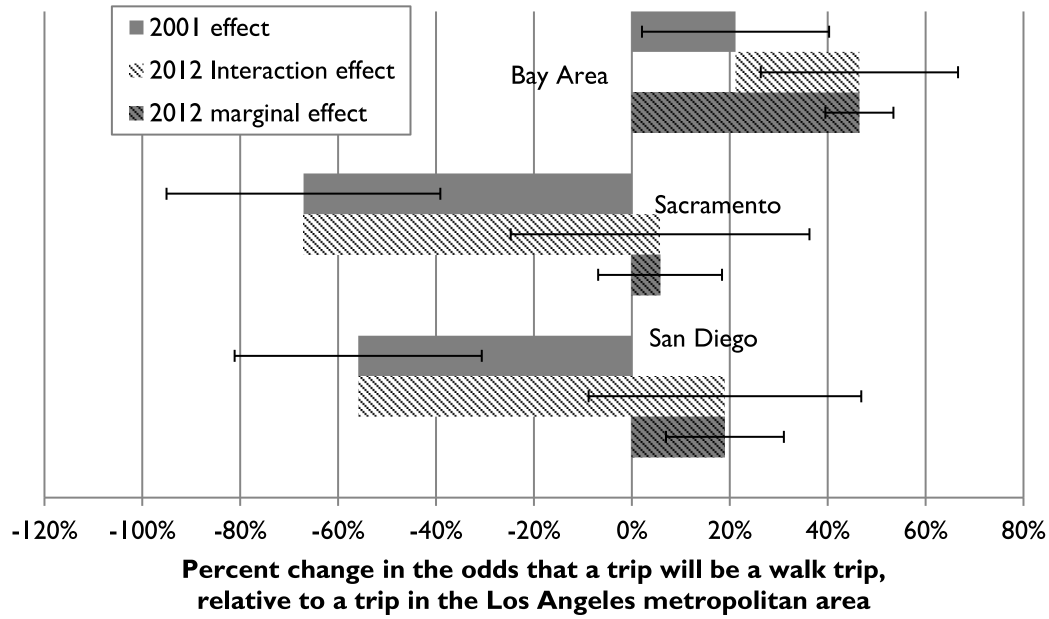


Figure 27 illustrates the differences in the odds of walking among metropolitan areas and between years. In 2001, a trip in the Bay Area was more likely to be a walk trip than a trip in the Los Angeles area was, and this difference had more than doubled by 2012. In 2001, trips in San Diego and Sacramento were both less likely than trips in Los Angeles to be walk trips. By 2012, this difference had disappeared in Sacramento and reversed itself in San Diego.

Figure 27. Effects of metropolitan area on the odds of walking



Discussion

In general, trip characteristics (trip distance and trip purpose) have the greatest effects on the odds of walking, and the magnitudes of these effects have increased between 2001 and 2012. Individual and neighborhood characteristics have more modest effects on the odds of walking, and these effects are consistent between the two survey years.

Table 10 identifies 18 different characteristics for which a change would be expected to increase walking mode shares (by increasing the odds that any particular trip will be a walk trip). For 12 of these 18 characteristics, the change that would have increased walking is the change that was observed. In fact, for three characteristics—trip length, the share of home-based fitness trips, and the share of the study population living in the Bay Area—not only did change occur in a direction consistent with increased walking, but the influence of these factors on walking also increased between 2001 and 2012, magnifying the effect of these changes. For four of the 18 characteristics where a change could have contributed to increased walking, the change that occurred was in the opposite direction to one consistent with more walking. However, in all four cases, the effect of that quantity on walking had either been eliminated or reversed by 2012.

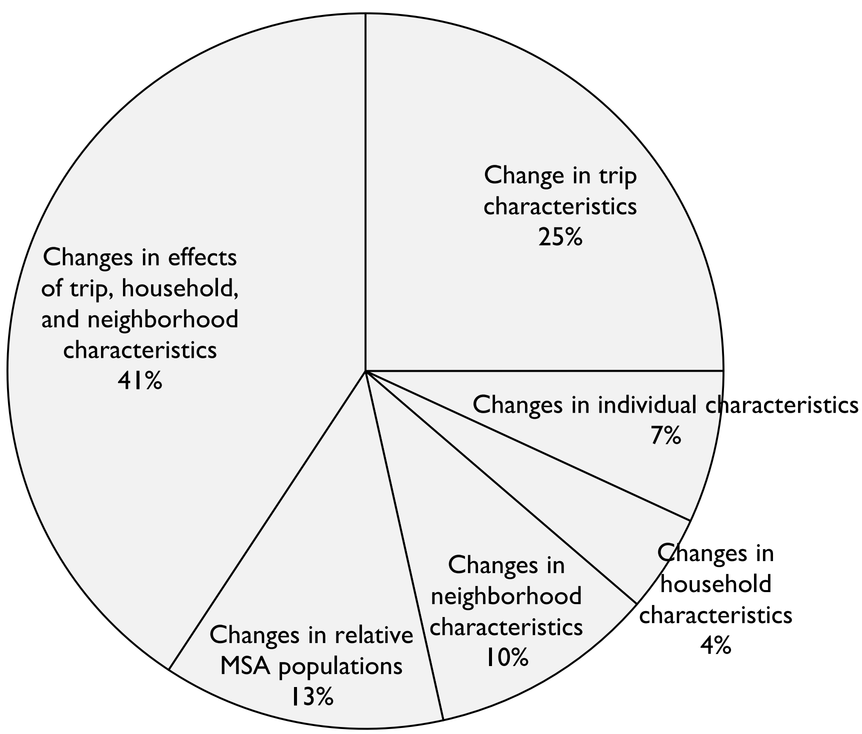
Taken together, these results suggest that several changes occurred within California metropolitan areas between 2001 and 2012 that contributed to the observed increases in walking. Further, we found no counterbalancing changes appear to have mitigated the effects of those changes. Moreover, since the effects of changes that contributed to increased walking were magnified and the effects that would have offset those were either eliminated or reversed by 2012, the actual increase in walking was greater than would have been predicted, even if analysts in 2001 could have accurately anticipated changes in the characteristics of trips, travelers, households, and neighborhoods that occurred.

Table 10. Changes that would be expected to increase walking and compared to actual changes

Variables	Change that would have increased walking	Change that occurred	Change in effect
Trip			
Trip length (miles)	Decrease	Decrease	Magnified
Trip purpose shares			
Non-home-based work	None	Decrease	None
Non-home-based other	Decrease	None	None
Home-based errands	None	Increase	None
Home-based shopping	Decrease	Increase	Eliminated
Home-based social/culture	Increase	Increase	None
Home-based dining	Decrease	Increase	Reversed
Home-based fitness	Increase	Increase	Magnified
Home-based school	None	Decrease	Magnified to positive
Home-based other	None	Decrease	Magnified to positive
Individual characteristics			
Percent female	None	Increase	None
Percent with driver's license	Decrease	Decrease	None
Percent employed	Decrease	Decrease	None
Percent with no disability	Increase	None	None
Percent foreign-born	None	Increase	None
Household			
Household size (people)	Decrease	Decrease	Diminished
Vehicles per driver	Decrease	Decrease	None
Income (log)	None	Increase	None
Percent with no children under 13	Decrease	Decrease	Diminished
Block-group			
Average activity density	Increase	Increase	None
Average home age	Increase	Increase	None
Average percent youth (age 18-24)	Increase	Increase	None
Metropolitan Area			
Percent living in Bay Area	Increase	Increase	Magnified
Percent living in Sacramento area	Decrease	Increase	Eliminated
Percent living San Diego area	Decrease	Increase	Reversed

We can fit the model coefficients to the original data to determine how much of an increase in walking the model predicts between 2001 and 2012, and compare that value to what the model would have predicted if the model coefficients for the interaction terms or trip, individual, household, and neighborhood characteristics had been zero. This allows us to estimate how much of the observed increase in walking can be explained by changes in trip, individual, household, and neighborhood characteristics and how much can be explained by changes in the relationship between these characteristics and the odds of walking. These proportions are illustrated in Figure 28. As shown, about 40 percent of the observed increase in walking can be explained by changes in the *relationships* between walking and each trip, individual, household, and neighborhood characteristic (for example, increased sensitivity to trip distance). The remaining 60 percent of the observed increase can be explained by changes the characteristics themselves (for example, reduced trip lengths, smaller household sizes, and higher densities), as well as changes in the relative shares of population living in each MSA (for example, the increased share of the study area population living in the Bay Area).

Figure 28. Increase in walking attributable to changes in trip, individual, household, and neighborhood characteristics



Differences in trip characteristics (trip distance and trip purpose) explain about a quarter of the observed increase in walking. Differences among the four metropolitan areas that are not otherwise accounted for in the model contribute another 13 percent of the observed increase. Changes in neighborhood characteristics (density, age of housing stock, and percent youth) account for 10 percent of the increase.

Conclusion

The findings of this study suggest two important insights that should inform local planning for pedestrians.

First, dramatic increases in walking are most likely to occur in connection with a confluence of factors. While many of the factors associated with increased walking are beyond the control of planners and policy makers, others may be influenced by planning and policy decisions. For example, more walk trips are likely to result from land use plans that bring origins and destinations closer together, especially for trip destinations that are already attractive for walking, such as entertainment, culture, fitness, and recreation destinations, including parks and open space. Likewise, improving the proximity of family- and child-oriented amenities, such as high-quality schools and childcare facilities can increase opportunities for walking by members of households with young children, who are already more inclined to walk than their peers. These types of changes that could serve to reduce trip distances could become increasingly effective in light of our finding that the decision to walk has become more sensitive to trip distance since 2001.

Second, the significant changes in the effects of our explanatory variables over time highlights the importance of frequent updates and recalibration of planning models that use these relationships to predict future travel demand, since these relationships are not constant over time. The danger of under-predicting walking mode shares is two-fold: first, it may lead planners and policy makers to inadequately invest in walking amenities that can make walking safer and more pleasant for the growing number of travelers who use this transportation mode. Second, failure to accurately predict walking travel demand may lead to overinvestment in far more expensive transportation infrastructure for motorized transportation modes.

There is a need for further research that examines changes in walking behavior over time. One barrier to conducting such studies is a paucity of detailed time-series data about the characteristics of built environment that are believed to influence the decisions to walk, such as the presence and quality of pedestrian amenities. A second barrier is the lack of frequent travel surveys that are designed to capture short, non-commute trips; these trips are the most likely to walk trips, but have not been the focus of traditional travel surveys that have emphasized regional travel. As data on travel and the built environment continue to improve in detail, consistency over time, and collection frequency, researchers will be in position to greatly improve the current understanding of the determinants of the decision to walk and factor that are most likely to cause changes in walking behavior.

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IV. Change, change, change: The relationship between changes in neighborhood characteristics and changes in walking

Introduction

Previous studies (Ham et al., 2005; Joh et al., 2015; Pucher et al., 2011; Santos et al., 2011; Simpson et al., 2003; Tudor-Locke et al., 2007) as well as our analysis in Chapter III show that rates of walking have increased over time. Yet only one of these studies analyzes whether *changes* in neighborhood characteristics might contribute to observed changes in walking mode choice within specific neighborhoods. This study seeks to address this gap in the literature by examining the relationship between changes in walking mode choice and changes in other neighborhood characteristics within California neighborhoods. To assemble a large enough sample of census tracts, we draw on data from the 2001 and 2012 California Household Travel Survey from throughout the state. We determine the change in walking mode choice in a sample of over 1,300 California census tracts, which are home to 20 percent of the state's population, and which included enough trips to perform this analysis. We then use a Tobit regression model to determine the degree to which these changes may be explained by changes over time in the socioeconomic and built environment characteristics of these census tracts.

We find that changes in two census tract characteristics are associated with changes in walking mode choice. First, walking and poverty rates are inversely related; a one percent reduction in the poverty rate within a census tract is associated with a 0.4 percent increase in walking mode share. Second, a one percent increase in intersection density is associated with a 0.75 percent increase in walking mode share. These findings suggest three types of policy efforts to increase walking mode shares: (1) policies to reduce poverty, (2) policies to minimize the effects of poverty on walking mode choice, and (3) development patterns characterized by high intersection density and pedestrian route directness.

Determinants of changes in walking mode share

Data from a variety of sources show an increase in walking mode share over time in the U.S. (See Appendix A for a summary of these studies.) The National Household Travel Survey (NHTS), a national inventory of daily travel in the U.S., shows that the percentage of trips taken on foot increased from 8.6 percent in 2001 to 10.4 percent in 2009 (Santos et al., 2011). There was also a 28 percent increase in the number people accessing transit by walking from 2001 to 2009 (Freeland et al., 2013). Due to inconsistencies in collecting data on walk trips, it is difficult to identify from previous national travel surveys the start of this upward trend (Clifton & Krizek, 2004). Traditional travel surveys tend to undercount short trips, many of which are taken on foot (Stopher & Greaves, 2007), and the NHTS only began specifically instructing survey respondents to report walk trips in 2001 (Santos et al., 2011). However, there is some evidence that walking mode shares in the United States have been increasing since as early as 1995. For example, in a study of short trips (one mile or less) Ham et al. (2005) find an increase in walking mode share between 1995 and 2001.

Walking rates have increased according to data from other studies, a finding that validates the trends from national travel surveys. For example, the Behavioral Risk Factor Surveillance System (BRFSS) is sponsored by a number of federal agencies including the Centers for Disease Control and Prevention, and is the nation's premier system of health-related telephone surveys. Data from the BRFSS show an increase in the prevalence of leisure walking from 1987-2000 (Simpson et al., 2003). Similarly, data from the American Heritage Time Use Study find an increase in the percentage of adults that walks for exercise from 2.9 percent in 1985 to 5.4 percent in 2003 (Tudor-Locke et al., 2007). The duration of time adults spent walking for exercise also increased from 30 to 45 minutes per day.

Increases in walking are not been uniform across population groups. Low-income adults, women, minorities, and working-age adults have experienced the largest increases in walking (Freeland et al., 2013; Pucher et al., 2011; Simpson et al., 2003). In contrast, rates of walking among seniors have lagged (Pucher et al., 2011). Data from the 2001 and 2009 NHTS show that the elderly (65 years and older) reported a decline across two measures – the percentage that walked per week (45 percent to 41 percent) and the percentage that took five or more walk trips per week (from 31 percent to 30 percent) (Pucher et al., 2011). Increases in walking also vary across cities. As might be expected, the percentage of workers that walk to work is highest in large, dense cities such as Boston (15 percent), Washington, DC (12 percent) and New York (10.3 percent) (McKenzie, 2014). However, among the largest 50 cities, only Atlanta, Boston, Chicago, Cleveland, Omaha, Sacramento, San Jose, and Seattle experienced statistically significant gains from 2000 to 2008-2012 in the percentage of people that walked to work (McKenzie, 2014).

Amidst these promising trends, these data suggest a few areas of concern. First, despite numerous planning efforts aimed at creating walkable, mixed-use communities, there has been a substantial decline in the percentage of commuters that walk to work. The walk commute share fell from 5.6 percent in 1980 to 2.8 percent in 2008-12 (McKenzie, 2014). This finding may or may not be troublesome since commute trips comprise only 16 percent of all trips (Santos et al., 2011). Second, perhaps more problematic is the fact that despite increases in walking, even people who are walking still are not active enough to meet national public health goals. Simpson et al. (2003) find no increase in the prevalence of people meeting the recommendation for moderate physical activity for at least 30 minutes per day, five or more days per week. Only 20 percent met this goal, a figure well below the 30 percent target.

All of these studies suggest that walking is becoming an increasingly important mode of transportation, but in order to ensure that these promising trends continue, planners and policy makers need a better understanding of the factors that explain the observed increases in walking. There is a large and growing body of research on the determinants of walking, much of it focused on the relationship between the built environment and walking behavior.[13] For the most part, these have been cross-sectional studies. While cross-sectional studies offer some insight into the effects that changes in individual, household, and neighborhood characteristics may have on changes in walking behavior, they are less relevant than longitudinal studies based on observed changes over time.

Of the longitudinal studies on walking behavior that have been completed, most have been limited in their geographic scope and have assessed the effects of specific interventions. Ogilvie et al. (2007) review 19 randomized controlled trials and 29 non-randomized controlled studies and find that:

> Interventions tailored to people's needs, targeted at the most sedentary or at those most motivated to change, and delivered either at the level of the individual (brief advice, supported use of pedometers, telecommunications) or household (individualised marketing) or through groups, can encourage people to walk more, although the sustainability, generalisability, and clinical benefits of many of these approaches are uncertain (Ogilvie et al., 2007, p. 1).

The most successful of these interventions increased walking by up to 30-60 minutes a week on average, at least in the short term. A few studies examine the relationship between infrastructure investments and walking. These studies suggest that safety improvements and the provision of high-quality, traffic-free walking routes increased walking; the largest effects were among individuals without automobiles (Boarnet et al., 2005; Goodman et al., 2014). Additionally, studies of household travel behavior before and after the opening of light rail systems find associations between light rail use and physical activity through walking (Brown et al., 2015; MacDonald et al., 2010).

A study by Joh et al. (2015) is unique; it is a longitudinal study of changes in walking behavior over a relatively large geographic area—the Los Angeles combined statistical area (CSA)—using geographic areas—46 regional statistical areas (RSAs)—as the unit of analysis. Rather than evaluating the effects of a specific intervention, they use a fixed-effects model to determine

[13] See Badland & Schofield (2005), Saelens & Handy (2008), Ewing & Cervero (2010), McCormack & Shiell (2011) for reviews of this literature.

effects of a variety of changes in socioeconomic and built environment variables. They find an association between increases in walking and increases in population, employment, and transit service densities.

Data and methodology

Our study is a longitudinal study with a similar approach to that of Joh et al. (2015): we use a geographic area—the census tract—as the unit of analysis to determine how changes in socioeconomic and built environment variables relate to changes in walking mode share over a period of approximately ten years. By using a smaller unit of analysis (census tracts) from a wider geographic area (the state of California), we are able to achieve a much larger sample size and examine changes in neighborhood characteristics with greater specificity. The selection of census tracts for inclusion in our sample is described later in this section.

This study uses data from the 2001 and 2012 California Household Travel Surveys (CHTS) to determine how walking mode shares have changed in neighborhoods throughout California between the two years. The California Department of Transportation conducts the CHTS approximately every ten years to collect travel data from households throughout California. Members of participating households completed travel diaries with detailed information about all trips and activities during a pre-assigned 24-hour period, where dates were assigned to ensure that data was collected for every day for a full year. Upon completing the travel diary, survey participants reported their travel through a computer-assisted telephone interview or by returning the travel diaries by mail.

Our analysis includes trips by adult survey respondents and, since the focus of our analysis was intra-metropolitan travel, we excluded from our analysis trips that were longer than 150 miles.

Table 11. Differences in sample sizes between survey years

Unweighted sample size	2001 Survey	2012 Survey	% change
Number of households	2,992	14,419	382%
Number of people	4,612	24,442	430%
Number of trips	20,248	93,918	364%

There were some important differences in the survey methodology between the two years. First, the survey sample size was much larger in 2012 than in 2001, as shown in Table 11. Second, trips were defined differently between the two survey years. In 2001, a trip was defined as a change in location with the purpose of participating in non-travel activities. Thus, trips with a purpose of changing transportation modes (walking to a transit station or a remote parking location, for example) were generally not included, nor were loop trips (for instance, going on a walk for exercise, where the trip begins and ends in the same location). In 2012, both mode-changing trips and loop trips were counted as trips. In order to compare travel between the two years, we removed all loop trips from the 2012 data set and linked all mode-changing trips together to identify the trips' ultimate origins and destinations. Walk trips were defined as trips for which all segments took place by walking.

The confidential data from the CHTS includes the latitude and longitude coordinates for each trip end. Using these coordinates, we geocoded each trip origin and assigned it to a census tract. For each census tract, we calculated the walking mode share by determining the proportion of trips originating in the tract that took place entirely by walking, using survey weights to adjust for any over- or under-sampling of particular regions or population groups. However, many tracts in the state did not contain any survey-day trip origins in one or both survey years, and many more included too few survey-day trips origins for calculated mode shares to be meaningful.

Table 12 shows the number of census tracts with enough trips to meet thresholds of one, ten, 20, and 50 survey-day trips in both survey years, and Map 2 illustrates the spatial distribution of these census tracts. Census tracts with the greatest number of survey-day trips were generally in the least-populous areas of the state, especially those that generate large numbers of trips by non-residents. For example, the greatest number of survey-day trips originating in a single tract for both survey years was near Yosemite National Park.

Map 2. Spatial distribution of California census tracts with enough survey-day trips in both years to meet selected thresholds

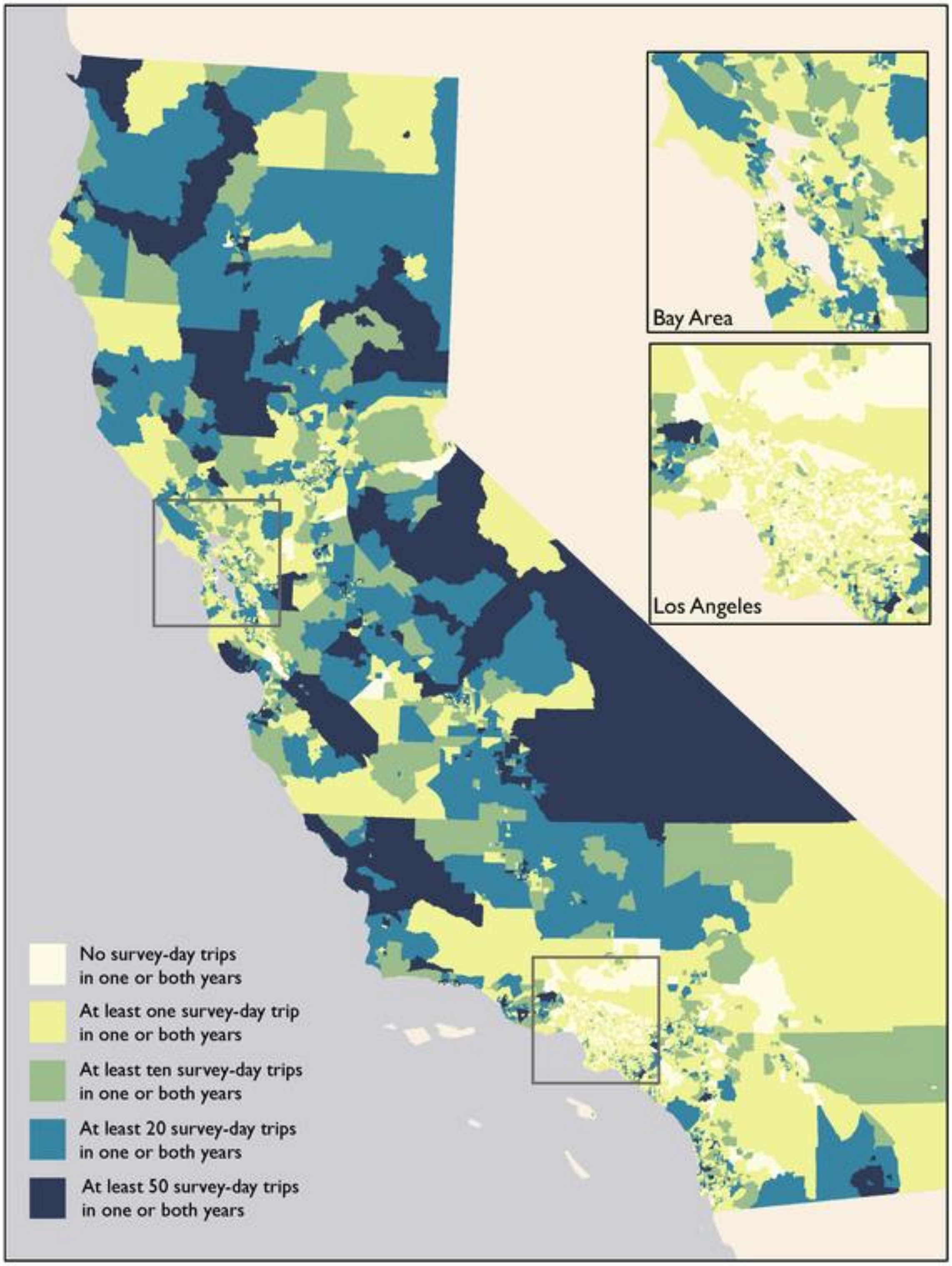


Table 12. Number of California census tracts meeting selected thresholds for survey-day trips

	2001 CHTS	2012 CHTS	Both Years
Number of census tracts in California (2010 boundaries)	8,057	8,057	8,057
Number of tracts with at least **1** survey-day trip origin	6,412	7,959	6,377
Number of tracts with at least **10** survey-day trip origins	2,951	6,609	2,783
Number of tracts with at least **20** survey-day trip origins	1,649	4,870	1,463
Number of tracts with at least **50** survey-day trip origins	575	1,884	429

In order to achieve a relatively large and diverse sample of census tracts while still using meaningful estimates of walking mode share, we included all census tracts with at least 20 survey-day trip origins in our sample.

Throughout this paper, percent change for any census tract characteristic is calculated based on the mid-point method, which yields values that can range from -200 percent to +200 percent:

$$Percent\ increase = \frac{(new\ value - initial\ value)}{\left(^1/_2\right)(new\ value + initial\ value)}$$

Over the entire state, the walking mode share increased from 5 percent in 2001 to 9 percent in 2012, representing a 56 percent increase. Table 13 shows the changes in mode shares within the sample tracts, and Figure 29 illustrates the distributions of the values in Table 13 and Map 3 shows the spatial distribution.

Table 13. Change in walking mode shares within sample tracts

	Mean	Median
2001 Walking mode share	5%	2%
2012 Walking mode share	8%	4%
Percent increase	45%	67%

For data on socioeconomic and housing characteristics of the census tracts in our sample, we relied on data from the 2000 and 2010 United States Census, tabulated into consistent 2010 census boundaries by Logan, Xu, and Stults (2014). We obtained street network connectivity data from Barrington-Leigh and Millard-Ball (2015). For some census tracts, the street network was too sparse to calculate street network connectivity, and those tracts were excluded from the sample, leaving a remaining sample of 1,303 census tracts. These tracts represent 16 percent of all census tracts in California and are home to 20 percent of the state's population.

Our sample of census tracts is not representative of all California census tracts: the most dense, urban census tracts appear to be the least likely to have been included in our sample. However, as shown in Table 13, the walking mode shares and increases in walking within the sample tracts and the increase in walking are comparable to those for the state overall.

Figure 29. Distributions of walking mode shares in sample tracts, 2001-2012

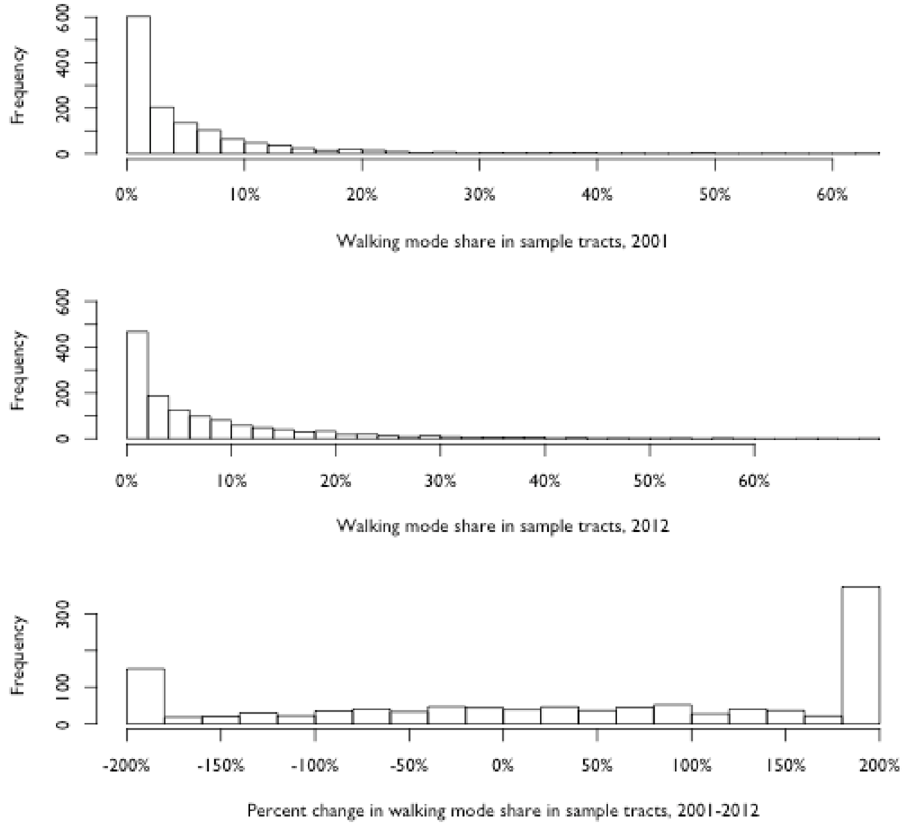
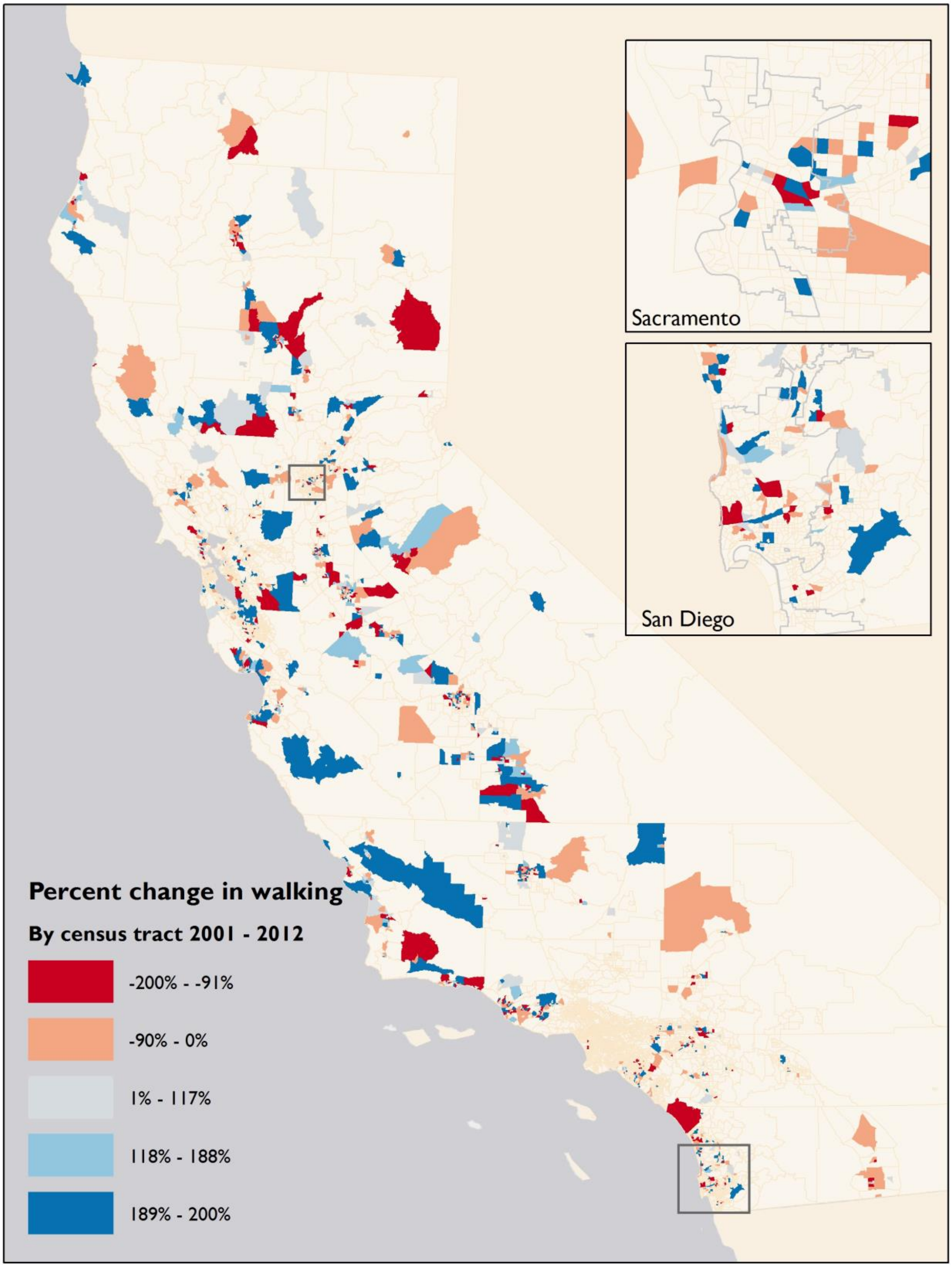


Table 14. Characteristics of tracts in study sample and within California

	Mean		Median	
	Sample tracts	California	Sample tracts	California
Socioeconomic characteristics				
Change in percent non-white	23%	16%	22%	15%
Change in percent under 18 years old	-19%	-11%	-9%	-11%
Change in percent over 60 years old	15%	18%	13%	17%
Jobs per person	-14%	-4%	-15%	-7%
Employment density	-4%	4%	-7%	-1%
Poverty rate	4%	-2%	5%	-1%
Network connectivity				
Change in intersection density	16%	20%	11%	14%
Change in percent dead-ends	6%	12%	3%	4%
Change in percent four-way intersections	11%	9%	5%	4%
Change in average nodal degree	< 1%	> -1%	> -1%	> -1%
Housing				
Housing unit density	15%	11%	7%	3%
Percent renter-occupied homes	11%	9%	7%	4%

Map 3. Percent change of walking mode shares in sample tracts, 2001-2012



As shown in Table 14, changes in network connectivity and housing characteristics within the sample tracts were similar to the changes in tracts throughout the entire state, as were changes in the racial and age characteristics of the tracts. The greatest differences between the sample tracts and the full set of California tracts are in the changes in tract economic characteristics.

To determine the relationship between changes in tract characteristics and changes in walking mode share, we ran a Tobit regression predicting walking mode share for trips originating in a census tract (censored at +/- 2.0, the minimum and maximum possible values for percent change calculated by the mid-point method) with independent variables selected from those listed in Table 14.

Table 15. Correlations between walking mode share and among its potential predictors

	Socioeconomic changes						Street connectivity changes				Housing changes		
	% non-white	% under 18	% over 60	Jobs per person	Job density	Poverty rate	Intersection density	% dead ends	% 4-way intersections	Average nodal degree	Housing unit density	% renting	Walk mode share
% non-white		0.14	-0.17	-0.03	0.03	0.12	0.04	-0.08	0.04	0.02	> -0.01	0.24	-0.02
% under 18			-0.15	-0.06	-0.01	-0.05	0.07	> -0.01	0.07	0.04	0.08	-0.16	0.02
% over 60				0.05	0.02	0.07	-0.01	-0.06	0.05	0.04	0.10	0.12	0.02
Jobs per person					**0.85**	0.05	-0.17	0.05	-0.03	-0.03	-0.30	0.01	0.02
Job density						0.02	0.09	0.02	> -0.01	-0.01	0.18	0.16	0.02
Poverty rate							-0.10	0.02	-0.03	-0.06	- 0.06	0.20	-0.08
Intersection density								-0.16	0.21	0.22	**0.42**	0.02	0.04
% dead ends									-0.23	**-0.60**	-0.06	-0.03	0.01
% 4-way intersections										**0.68**	0.05	> -0.01	< 0.01
Average nodal degree											0.05	-0.03	> -0.01
Housing unit density												0.31	-0.01
% renting													-0.07
Walk mode share													

Note: **Bold** text identifies relationships that are strongly correlated, greater than 0.33.

Table 15 shows the correlations among the variables considered for inclusion in the model, with bold text to highlight correlations with a magnitude greater than 0.33. The model excludes job density, housing unit density, percent dead ends, and percent four-way intersections, based on their correlations with other variables.

Since both the dependent variables and all independent variables are expressed in terms of percent change, the model coefficient estimates can be interpreted as elasticities: the percent change in walking that would be anticipated for a one-percent change in the independent variable.

Results

The results of the Tobit regression are summarized in Table 16. The model has an AIC score of 3917 and an R-squared value of 0.01. This suggests that only about one percent of the variation in changes in walking mode shares in the sample census tracts can be explained by changes in the built environment characteristics included in the model. This is not surprising; other studies (including the research included in this report) show that trip, individual, and household characteristics have a greater influence on mode choice than do neighborhood characteristics. Moreover, reliable historical data on built environment characteristics that are likely to influence walking mode choice —such as traffic congestion, the presence of sidewalks and crosswalks, and quality of transit service— were not available for inclusion in the model.

Table 16. Results of Tobit regression model predicting change in walking mode share

	Estimated elasticity of walking mode share with respect to the variable	Standard error	95-percent confidence interval			P-value
Percent non-white	0.15	0.41	-0.65	to	0.96	0.713
Percent under 18	0.36	0.42	-0.46	to	1.17	0.394
Percent over 60	0.40	0.28	-0.15	to	0.96	0.154
Poverty rate	**-0.34**	**0.13**	**-0.59**	**to**	**-0.10**	**0.007**
Percent rental homes	-0.40	0.29	-0.98	to	0.17	0.169
Jobs per person	0.15	0.15	-0.15	to	0.45	0.328
Intersection density	**0.52**	**0.26**	**0.00**	**to**	**1.04**	**0.048**
Average nodal degree	-1.42	1.46	-4.27	to	1.44	0.331

Two coefficients are significant at a 95-percent confidence interval: the change in the poverty rate and the change in intersection density. A one-percent increase in the poverty rate within a census tract is associated with a 0.34-percent decrease in a census tract's walking mode share. A one-percent increase in the number of intersections per acre is associated with a 0.52-percent increase in a census tract's walking mode share.

Discussion of results

The negative elasticity of walking mode share with respect to the poverty rate may be somewhat surprising, although the direction of the relationship is consistent with the findings from the longitudinal study of regional statistical areas of Los Angeles by Joh et al. (2015), which show a negative but statistically insignificant relationship between walking mode share and household income.

The monetary cost of walking is minimal compared to the costs of vehicle ownership and maintenance, or even compared to the cost of owning a bicycle or riding public transit. Thus, one might expect residents of low-income neighborhoods to be the most likely to travel by walking rather than by modes that incur greater monetary costs. Moreover, we calculated the correlation between 2010 census tract poverty rates and current walking accessibility as measured by Walk Score®, and found that neighborhood Walk Score® and neighborhood poverty rates are positively correlated, with a Pearson correlation coefficient of 0.43.

However, while the monetary costs of walking may be the lowest, the time costs of walking are the highest, since walking is the slowest mode. Many low-income neighborhoods are resource poor, lacking in proximate opportunities easily reachable on foot such as available employment, healthy food outlets, health-care services, social networks, and recreational facilities (Bostock, 2008; D'Angelo et al., 2011; Immergluck, 1998; Lovasi et al., 2009; Moore et al., 2008). Since residents of low-income neighborhoods are likely to be constrained not only in terms of money, but also in terms of time, greater reliance on motorized transportation may be a necessity. These findings, however, may be influenced by the way in which we assembled the data. Low-income adults are more likely to use transit than higher-income adults (Pucher & Renne, 2003) and, therefore, we expect that they are also more likely to make walk trips to access transit stops and stations (Besser & Danngenberg, 2005). However, short first- and last-mile walk trips are excluded from our analysis since it focuses on linked trips taken to access an ultimate destination.

The pedestrian environments in low-income neighborhoods may discourage walking. With respect to the relationship between Walk Score® and poverty, Koschinsky et al. (2016) compare Walk Score® with an alternative walkability index (the State of Place index) that incorporates characteristics of the built environment that are not captured by Walk Score®, including personal safety, traffic safety, and aesthetics. They find that the divergence between Walk Score® and State of Place is greatest in low-income neighborhoods. Similarly, in their study of low-income neighborhoods in New York, Neckerman et al. (2009:S264) find that poor census tracts "had significantly fewer street trees, landmarked buildings, clean streets, and sidewalk cafes, and higher rates of felony complaints, narcotics arrests, and vehicular crashes." Thus, low-income neighborhoods with high Walk Scores® may have less pedestrian-friendly environments than high-income neighborhoods with the same Walk Scores®. Both Walk Score® and State of Place are proprietary indices prepared and sold by for-profit firms (Koschinsky et al., 2016).

The inverse relationship between walking mode shares and poverty rates may be partially explained by perceptions of crime and safety in low-income neighborhoods. Studies show that low-income women's perceived lack of safety reduces their willingness to walk (Miles & Panton, 2006; Bennett et al., 2007). Participants in the Miles and Panton study expressed fears about being assaulted or harassed or that passers-bys would fail to help them should a problem arise. In a study of walking mode choice and crime rates in San Francisco, Ferrel et al. (2012) find that the odds of walking are 17 percent lower for work trips and 61 percent lower for non-work trips in high-crime areas, compared to low-crime areas. Yet, Joh et al. (2012) find that pro-walking attitudes are more common in areas with high crime rates than in areas with low crime rates. Together, these results may suggest that people living in neighborhoods with high crime rates are especially likely to increase the share of trips they make by walking as the crime rates in their neighborhoods decrease. However, no longitudinal studies have directly linked changes in walking mode shares to changes in crime rates.

Thus, travel by a more leisurely mode such as walking may be a luxury that is more available to residents of higher-income neighborhoods.

The elasticity of walking mode share with respect to intersection density is also statistically significant and suggests that a one-percent increase intersection in density is associated with a 0.75 percent increase in walking. This is almost double the elasticity of 0.39 that Ewing and Cervero (2010) find in their meta-analysis of seven cross-sectional studies that report a relationship between walking and street or intersection density. Intersection density increases the directness of walking routes, reducing walk trip distances and improving walking accessibility.

Conclusion

The results of this analysis suggest two specific policy directions that show promise for further increasing walking mode shares in neighborhoods throughout California.

First, despite research that suggests that residents of low-income neighborhoods have positive attitudes towards walking, we find that walking mode shares have increased the most in neighborhoods where the poverty rate has decreased. Thus, reducing poverty in California could serve to further increase walking mode shares throughout the state. However, as laudable as the goal of poverty reduction certainly is, it has proven to be difficult to achieve. In the meantime, efforts that focus on improving the pedestrian environment in low-income neighborhoods, with a particular focus on traffic safety and personal safety may serve to weaken the negative relationship between poverty and walking.

Second, the results of our longitudinal study suggest that the relationship between increases in walking and intersection density is even stronger than suggested in previous cross-sectional studies (Khan et al., 2014). Thus, planners can facilitate increasing walking mode shares by emphasizing increased intersection densities and better pedestrian route directness as neighborhoods are developed and redeveloped.

Finally, the lack of available data represents a major obstacle to conducting longitudinal studies of walking. First, our analysis was limited by the relatively small size of the 2001 CHTS which was approximately a fifth the size of the 2012 survey. The small sample size provided enough data (20 observations) at two points in time to analyze 18 percent of all California census tracts. Ideally, our analysis would half included larger samples within each tract over time and greater coverage across the state. Second, it is difficult to obtain detailed data on the pedestrian environment (e.g. safety, aesthetics, pedestrian amenities, etc.), a fact that was confirmed in our interviews with the staff of the four major California metropolitan planning organizations.[14] Moreover, there is no historical inventory of the characteristics of the pedestrian environment. Therefore, there is a need for more widespread and detailed data on these topics; and especially for archiving of such data to allow for comparisons over time.

[14] In Section 5, we report on our interviews with planners and regional travel demand modelers who work for the four major metropolitan planning organizations (MPOs) in the state – the Metropolitan Transportation Commission (MTC), Sacramento Area Council of Governments (SACOG), San Diego Association of Governments, and the Southern California Association of Governments (SCAG).

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V. Strutting into practice: Walking and travel demand modeling

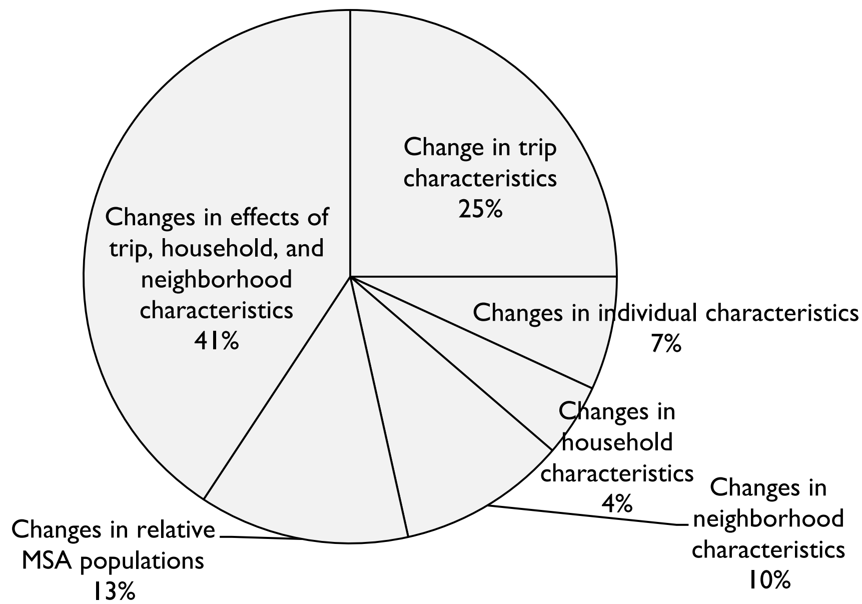
Introduction

As previously extolled throughout this report, walking is a good way for people to travel. Traveling by foot produces no greenhouse gas emissions, adds no congestion to the street or highway network, and is good for individual and public health (Frank et al., 2004; Murphy et al., 2007). Given these individual and societal benefits, cities, regional governments and metropolitan planning organizations have been working to increase the number of trips completed by walking. Enthusiasm toward walking has been aided by substantial increases in federal investments in active transportation – bicycling and walking (Fields & Cradock, 2015).

National data show an increase in walking rates (Ham et al., 2005; Joh et al., 2015; Pucher et al., 2011; Simpson et al., 2003; Tudor-Locke et al., 2007). Walking also has increased in California. As noted in previous chapters, the walking mode share in the four primary metropolitan statistical areas in California increased from 5 to 9 percent from 2001to 2012. As Figure 30 shows, and as previously described in Chapter 3, this growth has been related to two principal factors: (1) changes in the characteristics of the population and the communities in which they live and (2) changes in the effects of these characteristics on the likelihood of walking.

Given the benefits of and the increase in walking, metropolitan planning organizations (MPOs) would be wise to understand and incorporate walking into their analyses of regional travel to adequately plan for their regions. To what extent do MPOs already do this? More specifically, for this research, we examine how regional travel demand models—models that estimate the expected demand for transportation infrastructure—include walking and the factors related to this mode of travel.

Figure 30. Increase in walking attributable to changes in trip, individual, household, and neighborhood characteristics



As other scholars highlight, travel demand models often inadequately incorporate walking. In fact, many regional models in the United States do not forecast non-motorized travel at all (Singleton & Clifton, 2013). Singleton and Clifton (2013) reviewed the modeling framework for the 48 largest MPOs serving greater than one million people. The authors organized the MPOs into six categories. At the very top are MPOs that assigned walk and bicycle trips to the network; at the very bottom are those MPOs that do not model non-motorized travel. According to their framework, the MPOs in our study area (Bay Area, Sacramento, Los Angeles and San Diego) all do a reasonably good job of incorporating walking into their modeling efforts.

This study builds on the work of Singleton and Clifton (2013) through in-depth interviews with the four major Metropolitan Planning Organizations (MPOs) in California; the Metropolitan Transportation Commission (MTC), San Diego Association of Governments (SANDAG), Sacramento Area Council of Governments (SaCOG) and the Southern California Association of Governments (SCAG). All four MPOs were categorized near the top of Singleton and Clifton's (2013) spectrum.

Our research focuses on the following three questions:

1. How do current approaches to travel demand modeling incorporate walking behavior and pedestrian infrastructure?
2. How sensitive are travel demand models to changes in walking behavior and factors associated with walking behavior?
3. What, if any, improvements should be made to regional travel demand models to better integrate and understand walking?

We find that activity-based travel demand models are better suited to incorporating walking trips than the traditional four-step modeling approach. Three of the four[15] MPOs currently use activity-based models. However, even this approach can be strengthened with respect to the walking component of the models. Our interviews reveal the following and suggest potential improvements relate to five broad themes:

- ***Quality of mode choice data:*** Household travel surveys, the common building block for regional travel demand models, tend to underrepresent walking.
- ***Quality of the modeled relationship between capacity and demand***: The demand for walking and the capacity to accommodate this mode of travel are different for walking than for other modes. Regional travel demand models largely are used to make large infrastructure decisions and to shape regional transportation policy. As currently structured, they are not as useful in understanding and in making decisions regarding investments necessary to induce or improve walking.
- ***Quality of infrastructure data:*** There is no systematic inventory of the walking network and the quality of pedestrian infrastructure. As such, MPOs are hard pressed to quickly pinpoint where the pedestrian network needs to be improved.
- ***Geographic coarseness of large-scale models:*** Models are built to understand responses to larger-scale (e.g. regional) policies and projects than those that are necessary to induce or improve walking (which are more likely to be at the neighborhood level).
- ***Quality of route choice data:*** There are limited data on walking, particularly as it relates to the geography of walk trips. This gap inhibits model calibration and makes it difficult to identify specific intersections or corridors on the network where pedestrian volumes are likely to be high.

[15]SCAG, the only MPO not currently using an activity-based model, has one in development and reports to be making the switch within the next regional transportation plan update.

We expand on these themes as follows. We first define travel demand models, drawing from the literature on their purposes and relative merits. We then the approach we took in our interview process. We draw on these interview data in developing our major findings. Finally, the chapter concludes with a discussion of how planning agencies can improve their understanding of walking in the context of regional travel models.

Travel demand models: The basics

Travel demand models are tools to understand how current travel and future travel will be distributed across a regional network. They seek to answer questions such as: how many more trips can be expected due to population growth, where will those trips be located, and how will travel be distributed across different modes? As travel demand grows, the network must accommodate this growth. Consequently, Metropolitan Planning Organizations (MPOs) use the output of travel demand models to make decisions about transportation investments to best meet future needs.

To provide accurate predictions, travel demand models must accurately represent how people travel. Trips are assigned to the transportation network which, therefore, requires modelers to have accurate and detailed knowledge of the network. For example, they must have information on such elements as: the number of lanes on any particular street in the network, the number of turning lanes and the signal phasing, the length of highway on-ramps, etc. The modelers synthesize the location of people and their associated demographic characteristics, employment, and housing across the region. Travel demand modelers rely on these data to perform complex scenarios to simulate regional travel.

The model output is then used to develop potential scenarios related to future travel patterns and air quality, and to plan future infrastructure projects. For example, planners are interested in the potential answers to the following types of questions. How will travel shift if additional infill housing is created in certain locations? How will travelers likely respond to a new toll lane? If there is new transit service, from where will riders come? Planners can forecast future scenarios based on potential changes in the population, the transportation network, and the built environment.

There are two basic model types. The four-step trip-level model remains the dominant approach still used by most MPO's (Clifton et al., 2016). Activity-, tour-based modeling is a newer approach that provides a more representative understanding of individual daily travel (National Academies of Sciences, 2015). Trip-level models identify origins and destinations and assign trips to those locations. In contrast, tour-level models simulate travelers as they use the system and conduct all of their daily activities. The decisions this traveler makes are constrained by the number and type of activities and the available modes. In a trip-level approach, the model could estimate that 85% of trips at a particular employment location will be by driving. Using the tour- and activity-based approach, the number of trips by car at that location would depend on how many people arrived by car on that particular day. As described by one of our interviewees, the two model approaches should not produce different results at the macro level but rather, activity-based models provide a much greater level of detail. Drawing on the analogy of watching a television show in black and white versus color, one of our interviewees explained "it's still the same show. You just have a lot more nuance to what you're seeing."

While the two model types may produce similar overall results, activity-based approaches are generally viewed as the superior approach, particularly for walking (Davidson et al., 2007, Cervero, 2006, Singleton & Clifton, 2013, Clifton et al., 2016). Activity-based models understand walking is derived from an inherent need to perform individual and household activities. Thus, these models understand travel for more purposes than the commute; which we previous demonstrated is one of the least likely walking trip types. Secondly, activity-based models take into account travel trade-offs between members of a household, such as coordinating household vehicles. We similarly previously demonstrated how vehicle availability affects the choice to make trips by walking.

More generally, significant improvements in activity-based approaches include linking activities and travel, understanding time and space restrictions and incorporating characteristics of individuals into the decision-making process. Further, mode choices are constrained to a plausible range of options. For example, activity-based models assume that if a person did not travel by a car when they left on their first trip of the morning, this individual does not have a vehicle available for other trips during that day. Trips are not independent of each other; rather people have chains of trips, known as tours, and complete their necessary travel within those tours.

Limited technical and staff resources often hinder MPOs from moving to activity-based model approaches. Clifton and Singleton (2013) review the modeling approaches of the 48 largest MPOs in regions with populations greater than one million. They find that the four MPOs in our study areas all consider walking trips at some point in the modeling process and, in comparison to other large MPOs, give greater consideration to this mode. Our interviews build on this research by developing an in depth understanding of where additional improvements are required.

Methodology

We identified interviewees at each Metropolitan Planning Organization (MPO) related to our study area regions (see Table 17) by obtaining staff directories and referrals from agency staff.

Table 17. Metropolitan Planning Organizations selected for interviews

MPO	MPO geographic range	Study area region	Study area counties
Metropolitan Transportation Commission	9 counties: Alameda, Contra Costa, Marin, Napa, San Francisco, San Mateo, Santa Clara, Solano	Bay Area	Alameda, Contra Costa, Marin, San Francisco, San Mateo
Sacramento Council of Governments	6 counties: El Dorado, Placer, Sacramento, Sutter, Yolo, Yuba	Sacramento	El Dorado, Placer, Sacramento, Yolo
Southern California Association of Governments	6 counties: Imperial, Los Angeles, Orange, Riverside, San Bernardino, Ventura	Los Angeles	Los Angeles and Orange
San Diego Association of Governments	San Diego county	San Diego	San Diego

Our target was to interview two staff with different perspectives on regional travel demand modeling – one staff member who is directly involved with the modeling and a second who uses the model output in planning applications. In some cases, one interviewee would recommend the other. We conducted seven of eight interviews in-person. Each interview lasted approximately 45 minutes. The interview instrument is included in Appendix F. We transcribed each interview and then coded the transcripts to identify themes across the various questions. The themes reflect where interviewees made insightful points beyond pro-forma answers.

Quality of mode choice data

Household travel surveys are the primary input for information about trip making in the travel demand models. The surveys provide information about how far people travel, by which mode, and for what purpose. In turn, these data help to understand household trip generation and, further, to help understand the dynamic relationships among travel patterns, demographics, and land use. After the model is developed, household travel survey data provide a reference point for model validation.

Some interviewees voiced concern about these data. Sample sizes are small and the data can only be as good as the participant's memory and record keeping. One interviewee states:

> "We are kind of comparing our data to make sure our assumptions are reasonable especially when we have sketchy data sources, which the household travel survey usually are."

Their comments echo the critiques of other scholars. For example, Wolf et al. (2003) estimate that travel surveys underreport as much as 60% of trips, with the majority of these fairly short trips. Walking trips are short; in our four metropolitan areas the average walk distance is about ½ a mile and has declined over time (See Chapter 3 for a discussion of changes in trip distance from 2001 to 2012). Since walking trips are the shortest, concerns about general non-representation of travel in the survey data are likely much worse for walking trips (Houston, et al., 2014).

Regional demand models can only accurately estimate travel if reliable travel patterns are reflected in the household survey data. Monitoring the household travel survey process is essential to ensuring the accuracy of regional models.

The California Department of Transportation (Caltrans) greatly increased the sample size of the most recent statewide household travel survey. While a larger sample does not correct for the under-reporting of walk trips, it provides greater representation of the population, limits the influence of outliers, and allows for analysis of statistical difference. As noted in Table 18 the number of households with completed travel diaries more than doubled between the 2001 and 2012 surveys.

Table 18. Number of households between CA travel survey years

Survey Year	Households
2001	17,040
2012	42,431

As explained by Stecher et al. (2014), the existence of a pooled funding consortium between state agencies and eight regional partners increased the budget allocated to the survey, leading to a larger sample size. Further, this partnership allowed for the use of a more comprehensive survey instrument than any of the regions would have been able to produce on their own. In the future, conducting these surveys as a collaborative state-wide effort would lead to more detailed, reliable data on walking. Such data would help local regional and state agencies to better understand trends in walking and the factors that influence them.

Quality of the modeled relationship between capacity and demand

Regional travel demand models serve, first and foremost, a federal statutory purpose: conformity with the federal Clean Air Act. Additionally, interviewees spoke about a second and related purpose, the importance of having a tool for measuring how future projects or packages of projects will perform. One interviewee stated:

> "The RTP [regional transportation plan] process requires you to have some kind of modeling framework in order to evaluate the outcomes of your investments"

Another interviewee commented:

> "You're making a lot of decisions in the present about investments and policies that will influence the future in a big way in theory. And you want to base those decisions in the here and now on the best information you can bring...So the travel models fill that void….[the model] creates information that is not really available in the real world and it fills in for a lot of that information needed for people who have to make decisions now."

One interviewee provided an explanation for the lack of attention to walking: "We have to keep the travel model relevant to the policy questions that are being asked."

The use of regional models to plan investments may work better for motorized traffic and, to a lesser extent, for bicycling compared to walking since traveler response to changes in infrastructure are fairly well understood. MPOs can use model results to forecast the number of people likely to use a transit line or a particular transit station. Similarly, these models can help forecast traveler responses to tolling or travel demand management strategies (National Academies of Sciences, 2006; Davidson et al., 2007).

However, interviewees recognized that the decision to walk is likely to be based on a wider variety of factors than simple cost and travel time. Thus, the causal links between the decision to make a walk trip and capacity of the pedestrian network is quite weak —particularly when pedestrian infrastructure is represented at the level of detail that is typical for regional travel demand models.

Walking trips are less strongly linked to infrastructure availability than all other modes. For example, a car or transit vehicle cannot travel on a street without a lane; but someone could walk on a street without a sidewalk.

In the meta-review of the built environment and walking, only four studies correlated walking to sidewalks (Saelens & Handy, 2008). More studies found relationships between both aesthetics and accessibility than sidewalks.

Can the model answer relevant policy questions specific to walking? For example, can regional travel demand models give a reasonable estimate for how many more people will walk if a sidewalk is installed or improved?

In short, the answer is no. Interviewees noted that walking trips are linked to areas of higher density, with a greater number of destinations in close proximity to large amounts of people and a connected street grid as determinates of walking. The availability of sidewalks may matter in these cases, but interviewees did not believe that they are not the driving force.

Interviewees asserted that without a simple link between infrastructure and demand, MPOs are likely to find it difficult to use these regional travel demand tools for evaluating and ranking different policy questions about walking. They commented:

> "So are we capturing the value of investments in amenities on the pedestrian side? Probably not."

> "This time for the first time, we'll be assigning bike trips and ped trips will be locating them on the network. But then the question, is ok, are we assigning them Are we assigning them in the right place? We still don't have great data sources on either side to know. The bike data is getting better. And the ped data, we'll likely just look at [the output] to make sure people are walking more in the places we expect them to be walking more."

The weak causal link between the demand for walk trips and the capacity of the pedestrian network is not the only obstacle to applying regional travel demand models to understanding walking trip rates and walking mode choice. Gaps in representations of the walking network and the large scale of the models' geographic units of analysis are additional issues. We further explain these issues in the following sections.

Quality of infrastructure data

Travel demand models also have difficulty predicting walk trips because of gaps in representation of the walking network. Imagine opening your navigation system in a car and finding no roadmap. You would be lost. You would think, 'how can I get to my destinations without knowing where the streets are located?' While information about the road network is widely available, information about characterizing the pedestrian network is not. The lack of information on the walking network hinders the ability of modelers to assign walking trips to particular locations.

MPOs have to assemble information about the pedestrian network throughout the region. Data about the roadway network can be purchased by any number of third-party navigation companies. Transit information can be accessed through the nationwide Google Transit Feed Specification (for most places) or directly from transit operators. Finally, cities often have geographic data on the bicycling network. From where does information about the pedestrian network come?

As our interviewees note, in general, MPOs are missing these data:

> "The missing part is the infrastructure for walking. It is very difficult to get the sidewalk information to reflect infrastructure"

> "We don't know how many of those streets have sidewalks. We don't have [data on] how many of those streets have a landscape strip that buffers a pedestrian from noise on the street or perceived safety on the street, or whatever. So we have a street pattern variable which influences walking but we don't have anything that's a true pedestrian environment variable."

Some MPOs have a basic representation of the sidewalk network. However, are sidewalks the only information relevant to understanding walking? Studies suggest that other characteristics of the walking environment may be important such as land use mix, density of destinations, small blocks and high intersection density (Cervero & Duncan, 2003; Saelens & Handy, 2007). Understanding these relationships is important for the allocation of scarce transportation dollars to improve the pedestrian environment. MPOs should not wait to allocate funds until they have developed a detailed pedestrian network. But they ought to develop better and more fine-grained approaches to representing the walking network.

Geographic coarseness of large-scale models

As suggested by the name, regional travel demand forecasting models generate information about large areas. In the case of the Southern California MPO, SCAG, the region covers 38,000 square miles. Regions must be sub-divided into smaller parts; the most common sub-regional units used for this purpose are "traffic analysis zones" (TAZs). TAZ boundaries are generally designated by the MPO with the intention that they should be small enough that most trips occur between TAZs, rather than within TAZs, since within-TAZ trips are not assigned to the network. Thus, the geographic area of a TAZ will be a function of the typical expected length of trips beginning and ending there. As a result, TAZs are large in sprawling outlying areas and small in dense urban cores as each unit tries to each represent generally the same amount of information and are generally akin to the size of a census tract.

Regional demand models generate travel intensities at this geographic level and further attempt to assign trips to the network itself. MPOs have improved their models by increasing the total number of TAZs and reducing their size. For example, in the Bay Area, MTC's next model iteration will have a 60-fold increase in the number of TAZs. An interviewee from this region explained:

> "Our current model has 1450 TAZs. The next version will have 60,000 so that is a 60x increase. And once you do that, there's a lot of things that just change in how you represent behaviors because you have a lot more detail."

But is this spatial unit of analysis—the TAZ—appropriate for understanding walking? Smaller units help to more accurately reflect the location of built environment characteristics. Think of a neighborhood with a dense commercial corridor and single family homes. If this neighborhood is one large area, access to these destinations will be averaged over the entire neighborhood. In reality, people further away from the destinations are less likely to walk compared to residents who are more proximate to these commercial destinations. Smaller units allow for a more nuanced depiction of the built environment and, therefore, are better at capturing and describing short distance trips made by foot.

Quality of route choice data

A final obstacle to incorporating walking into regional travel demand models is the absence of pedestrian volume data at the intersection level. Transportation agencies at the local, regional, and state levels routinely collect vehicular traffic volume data. Traffic volume data can be used to calibrate regional travel demand models so they can accurately reflect drivers' route choice decisions. For example, at what point will congestion delays cause drivers to divert to less direct routes? Absent this information, the travel demand model could indicate approximately how many vehicles travel from one part of the region to another, but could not indicate which roadways they would use and where additional capacity might be needed.

Our interviews indicate that, across all regions, MPOs are operating their travel demand models without adequate data that would allow them to calibrate their models to accurately assign pedestrian trips to their most likely routes. The household travel survey can provide a general picture of how much overall walking occurs in the region and even within specific areas. However, this survey does not provide information about which paths and intersections pedestrians use. As a result, even in the case where a TAZ is the size of one city block, no information exists as to where a particular safety improvement should be located in that space to maximize its effect.

This deficiency highlights the difficulty in using regional travel demand models to assess future projects' effects on travel. And further, the main point of concern for MPOs to understand walking may not lie in the modeling approach itself; whether basic or sophisticated four step or the more advanced activity based approaches. Rather, the lack of a complete picture of walking, from the incomplete network representation to the intensity at specific intersections, places this mode at a major disadvantage in this key decision support tool.

Discussion and conclusion

Walking is a simple way to get around, but modeling this simple mode is quite complicated. While the major California MPOs are doing a better job of analyzing walking than most large MPOs in other parts of the country, there is much room for improvement.

Since regional travel demand models are often the basis for allocating funds for future transportation investments, improvements to walking infrastructure are at a disadvantage because obstacles to walking go far beyond a lack of capacity, and include factors such as comfort and safety that are difficult, and perhaps impossible, to incorporate into large-scale regional models. Nothing in the modeling framework is going to correct for this problem. However, an awareness of this conundrum where one mode is distinctly different than others may have the potential to begin addressing this issue.

Based on the results of our interviews, we recommend four distinct ways to improve how regional governments understand and plan for walking:

1. State and regional agencies ought to continue to support statewide efforts to collect household travel data

   Similar to a popular television commercial, we also believe more is better. If more households complete the survey, the dataset will include more trips. A larger dataset will help to seed the regional models with more information about diverse types of trips. The resulting model results are likely to be more accurate if they have a richer dataset as their foundation.

   A continued partnership between state and regional agencies may provide the resources necessary to explore other data collection strategies. For example, collecting data via GPS rather than by survey and individual recall will likely improve the accuracy of the data, particularly for short trips and/or trips that are taken only occasionally.

2. Develop and maintain a dataset on sidewalks

   Travel demand models are only as good as the information that goes into them. Most of the MPOs do not have basic information about the availability of sidewalks. This is not uncommon, since municipalities often struggle to build and maintain this type of a dataset (Grossman et al., 2014). Sidewalks are the most basic component of walking infrastructure. Thus, governments need to have information about their quality and allocation.

As rates of walking continue to increase, sidewalk availability and quality will be increasingly important. Regional transportation plans and funding can assist in improving sidewalk allocation and quality. However, to do so, planners must have information on where people walk and identify infrastructure problems.

3. Collect information about pedestrian locations and volumes across the region

   None of our MPOs were able to confidently validate their model output for walking trips. This again puts walking at a disadvantage because MPOs may not be able to identify where people walk and plan for safety improvements.

   Understandably, collecting pedestrian volume data is not as simple as collecting vehicle data. Cities cannot lay down a tube across the sidewalk akin to how car traffic data are collected. But the technology for collecting pedestrian data is quickly improving. MPOs should pay close attention to these new technologies and potentially incorporate them into other traffic volume data collection efforts.

4. Continue to exchange ideas about modeling improvements

   Many of the interviewees knew each other. They also noted the information exchange that occurs between MPOs, particularly MPOs in close proximity. As previously referenced by Singleton and Clifton (2013), the MPOs in our study areas are some of the national leaders in forecasting pedestrian behavior. Continual collaboration between these forward-thinking MPOs can potentially enhance efforts to better plan for walking. Further, these leaders can assist other smaller MPOs that may be less advanced in their representation of walking and non-motorized travel behavior.

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Appendix A. Studies on changes in walking in the United States

Study	Data	Measure	Major Findings
Brown et al. (2015)	• Before (2012) and after (2013) data collected using accelerometers and global positioning system (GPS) loggers in Salt Lake City, Utah • Lived w/i 2 km from planned light-rail extension	• changes in accelerometer counts per minute (cpm), in moderate to vigorous physical activity (MVPA) and light and sedentary physical activity	• New riders gained accelerometer-measured cpm than never-riders, gained 4.2 MVPA minutes, lost 12.8 sedentary minutes • Former riders had fewer cpm, lost 6.4 minutes of moderate-to-vigorous PA, gained 16.4 minutes of sedentary time
Gordon-Larsen et al. (2009)	• Coronary Artery Risk Development in Young Adults (CARDIA) Study, 1985-86, 1987-88,1990-91, 1992-93, 1995-96, and 2000-01	• Walk score: derived from walking items in physical activity questionnaire	• Decline in walk over time • Women walk more than men
Joh et al (2015)	• Southern California Association of Governments (SCAG) 2001 Post-Census Regional Travel Survey • California add-on sample of the 2009 National Household Travel Survey	• Walk trip share • Walk trip rate	• Increase in walk trip share of 4.42 percent • Increase in walk trip rates by 0.21 daily walking trips per person
Ham et al. (2005)	• 1995 Nationwide Personal Transportation Survey, 2001 National Household Travel Survey	• % of walk trips <= 1 mile for transportation (adults) • % of walk trips <= 1 mile to school (youth)	• Increase in walking among adults and youth • Largest increase among those with the lowest incomes
MacDonald et al. (2010)	• Data collected before (2006/07) and after (2008) the completion of the LRT system in Charlotte, NC • Lived w/i one-mile radius of LRT line	• Meeting weekly recommended levels of physical activity	• Use of LRT is related to increased odds of increasing one's physical activity through vigorous exercise • The association between LRT use and meeting weekly RPA levels of walking was in the positive direction but not statistically significant.
McKenzie (2014)	• Census: 1980, 1990, 2000 • American Community Survey: 2008-2012	• % walk to work	• Declined from 5.6 in 1980 to 2.8 in 2008-12
Pucher et al. (2011)	• 2001 and 2009 National Household Travel Survey	• Share of trips by walking • 30+ minutes of walking/cycling, • 30+ minutes of walking/cycling in bouts of 10+ minutes each	• Substantial increase in walk trips (from 8.6% to 10.5%) • Individuals 15+ made 17 more walk trips in 2009 than in 2001, • walking about 5 more hours and 9 more miles • Largest increase among working-age population

Studies on Changes in Walking in the United States (continued from previous page)

Study	Data	Measure	Major Findings
Simpson et al. (2003)	• Behavioral Risk Factor Surveillance System (BRFSS), 1987-2000	• Prevalence of leisure walking	• Increase in walking • Prevalence of walking 3x per week remained the same • Increase largest among women and minorities
Tudor-Locke et al. (2007)	• American Heritage Time Use Study, 1985 and 2003	• % of individuals that walk for exercise • Duration of walk for exercise	• Increase in % from 2.9 to 5.4% of adults • Increase in duration from 30 to 45 minutes/day
U.S. Department of Transportation (2010)	• 2001 and 2009 National Household Travel Survey • 2002-2008 American Community Survey	• % of trips by walking (NHTS) • % who commute by walking (ACS)	• Increase in number of walk trips by 25 percent • % of trips by walking increased to 10.9% • Increase in walking commuters from 2.48 to 2.82%
U.S. Government Accountability Office (2015)	• 2005 and 2013 American Community Survey	• The number of adults that commute by walking	• 21 percent increase in the total number of walking commuters (3.3 million to 4 million)

Appendix B. Alternative model results

	95-percent confidence intervals for coefficient estimates		
Variables	**Both years**	**2001**	**2012**
Trip			
Trip length (miles)	-2.04 - -2.14	-0.96 - -1.15	-2.28 - -2.40
Trip purpose (base: Home-based work)			
Non-home-based work	-0.01 - 0.29	-0.25 - 0.45	< 0.01 - 0.33
Non-home-based other	-0.92 - -0.65	-1.17 - -0.52	-0.92 - -0.62
Home-based errands	-0.42 - -0.15	-0.63 - 0.02	-0.42 - -0.12
Home-based shopping	-0.27 - 0.01	-1.06 - -0.33	-0.18 - 0.13
Home-based social/culture	0.19 - 0.50	0.10 - 0.85	0.18 - 0.52
Home-based dining	-0.01 - 0.33	-1.17 - -0.19	0.12 - 0.50
Home-based fitness	1.82 - 2.11	-0.03 - 0.95	1.98 - 2.31
Home-based school	0.43 - 1.04	-0.65 - 0.57	0.59 - 1.32
Home-based other	0.06 - 0.69	-0.44 - 0.65	0.09 - 0.87
Individual characteristics			
Age	0.01 - 0.03	-0.03 - 0.02	0.02 - 0.04
Age squared	-4×10^{-4} - -2×10^{-4}	-2×10^{-4} - 2×10^{-4}	-5×10^{-4} - -3×10^{-4}
Female (base: Male)	-0.10 - 0.02	-0.22 - 0.10	-0.11 - 0.01
Driver's license (base: Unlicensed)	1.59 - 1.81	1.20 - 1.76	1.63 - 1.87
Employment (base: Employed)			
Looking for work	0.05 - 0.31	0.11 - 0.65	-0.01 - 0.29
Not a worker	0.12 - 0.26	-0.02 - 0.44	0.11 - 0.27
Disability status (base: No disability)			
Mobility disability	-0.78 - -0.40	-0.93 - 0.17	-0.84 - -0.44
Other disability	-0.83 - -0.45	-0.75 - 0.23	-0.93 - -0.51
Foreign-born (base: Native-born)	-0.01 - 0.13	-0.38 - 0.08	< 0.01 - 0.16
Household			
Household size (people)	-0.15 - -0.09	-0.36 - -0.16	-0.13 - -0.07
Vehicles per driver	-0.79 - -0.65	-0.74 - -0.42	-0.84- - -0.68
Income (log)	-0.05 - 0.03	-0.10 - 0.14	-0.06 - 0.02
Youngest person (base: Adult)			
Baby	0.25 - 0.63	0.90 - 1.92	0.09 - 0.49
Toddler	-0.06 - 0.22	0.52 - 1.28	-0.19 - 0.11
Child	-0.06 - 0.14	0.28 - 0.86	-0.14 - 0.08
Teen	-0.33 - -0.09	-0.89 - 0.09	-0.33 - -0.07
Trip destination block-group			
Activity density (log)	0.15 - 0.23	0.07 - 0.25	0.15 - 0.23
Average home age (decades)	> -0.01 - 0.04	-0.06 - 0.08	> -0.01 - 0.04
Percent youth (age 18-24)	0.03 - 0.09	-0.04 - 0.12	0.3 - 0.10
Trip origin block-group			
Activity density (log)	0.15 - 0.23	0.08 - 0.26	0.16 - 0.24
Average home age (decades)	0.02 - 0.06	0.02 - 0.16	0.02 - 0.06
Percent youth (age 18-24)	0.05 - 0.11	> -0.01 - 0.16	0.04 - 0.11
Metropolitan Area			
Base: Los Angeles			
Bay Area	0.38 - 0.52	-0.07 - 0.35	0.40 - 0.54
Sacramento	-0.15 - 0.07	-1.03 - -0.47	-0.07 - 0.19
San Diego	-0.06 - 0.16	-0.84 - -0.34	0.07 - 0.31
Year			
2012 (base: 2001)	0.33 - 0.42	NA	NA

Note: Gray text indicates that the 95-percent confidence interval includes zero, so the coefficient is not significant at a 95-percent confidence level.

Appendix C. Walk Score®, neighborhood type, and sprawl

This appendix provides a summary of the built environment characteristics used in this study—Walk Score®, neighborhood typology, and other built environment indicators. We provide summary data for the study area and for each of the four MSAs. In Appendix D we provide summary Walk Score® data by county.

Walk Score®

We evaluate the mean Walk Scores® and distribution across counties, MSAs and overall study area. In our land area and population analysis, we assess the distribution of land area (in square miles) and population across the four Walk Score® categories: car-dependent, somewhat walkable, very walkable and walker's paradise areas. To calculate these percentages, we removed eight block groups that did not have Walk Score® labels.

Overall study area

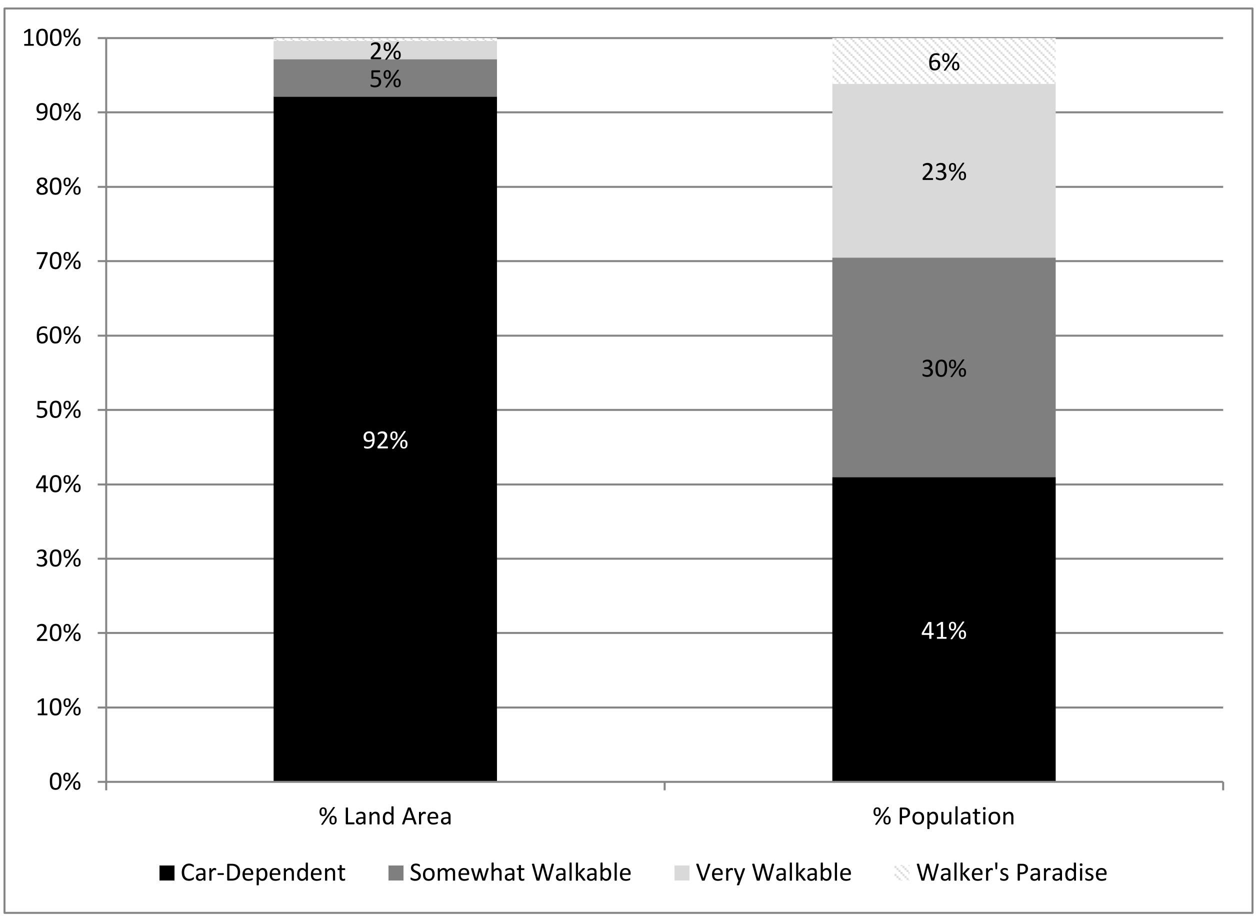
The average Walk Score® for our overall study area is 53.9 (SD 24.9), which is classified as somewhat walkable. The distribution of Walk Scores® appears close to normal, skewing slightly to the right, with the majority of block groups falling between 60 and 80. This pattern of Walk Scores® holds across most of the Walk Score® subcategories: dining and drinking, errands, schools, and shopping. There are a few notable exceptions. The parks and grocery Walk Score® distributions are much flatter.

In terms of total land area and population, more than 90 percent of the land within our study area is considered car-dependent and more than 40 percent of the population lives where most or all errands require a car. Only 5 percent of the study area can be characterized as somewhat walkable, and roughly 30 percent of the population lives in these areas. Very walkable areas constitute half as much land as somewhat walkable areas, 2.46 percent, and are home to 23 percent of the population. Finally, only 0.39 percent of the total study area can be classified as walker's paradise, and only 6.17 percent of the population lives there. As shown in Figure 1, the population within our study area living within each of the Walk Score® categories is much more evenly distributed than the land area. Densely populated areas with higher Walk Scores® most likely explain why this differs from land area, which is overwhelmingly car-dependent.

Table 19. Percent land area and population by Walk Score®--Overall study area

Walk Score®	# Block Groups	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	5,758	39,674,913,346	10,064,420	92%	41%
Somewhat Walkable	4,272	2,156,432,632	7,256,705	5%	30%
Very Walkable	3,409	1,060,329,573	5,736,806	2.6%	23%
Walker's Paradise	863	169,607,836	1,515,818	0.4%	6%
Total	**14,302**	**43,061,283,387**	**24,573,749**	**100.00%**	**100.00%**

Figure 31. Composition of land area and population by Walk Score® categories



MSA

Of the four metropolitan regions included in our study, Los Angeles had the highest mean Walk Score® (53.9) followed closely by the Bay Area (57.3). Los Angeles showed a normal distribution with most scores falling in the somewhat- to very-walkable range, between 60 and 80, while the Bay Area appeared flatter, with the greatest number of walker's paradise scores. San Diego had a mean Walk Score® of 43.9, and showed a flatter distribution with a higher number of car-dependent scores. Sacramento had the lowest mean Walk Score® (37.4), with more car-dependent block groups skewing the distribution to the left.

Table 20. Walk Score® —Study area and MSA

Metropolitan area	Mean	Standard Deviation
All combined	53.9	24.9
Los Angeles	57.4	22.3
Bay Area	57.3	28.0
Sacramento	37.4	21.9
San Diego	43.9	26.0

All of the MSAs are dominated by car-dependent land uses. Los Angeles, despite its car-centric reputation, actually had the least percentage of land characterized as car-dependent, roughly 83 percent, home to roughly a third of the population. Somewhat walkable areas comprise about 11 percent of the land area and also are home to just over a third of the population. The remaining 6 percent of land falls under the very walkable conditions or better, with less than 1 percent of land being walker's paradise. While more than a quarter of the Los Angeles MSA population lives in very walkable areas, less than 5 percent live in walker's paradise.

By contrast, the Bay Area, while having a higher percentage of car-dependent land area than Los Angeles, nearly 90 percent, also had the highest percentage of walker's paradise land area and the most people living there, almost 15 percent of the population. Another quarter of the population lives in very walkable areas, thus nearly 40 percent of Bay Area residents live in areas ideal for walking. The distinction between Los Angeles and the Bay Area occurs less in car-dependent category and more so in the number of people that live in highly walkable areas. There is substantially more somewhat walkable land in Los Angeles.

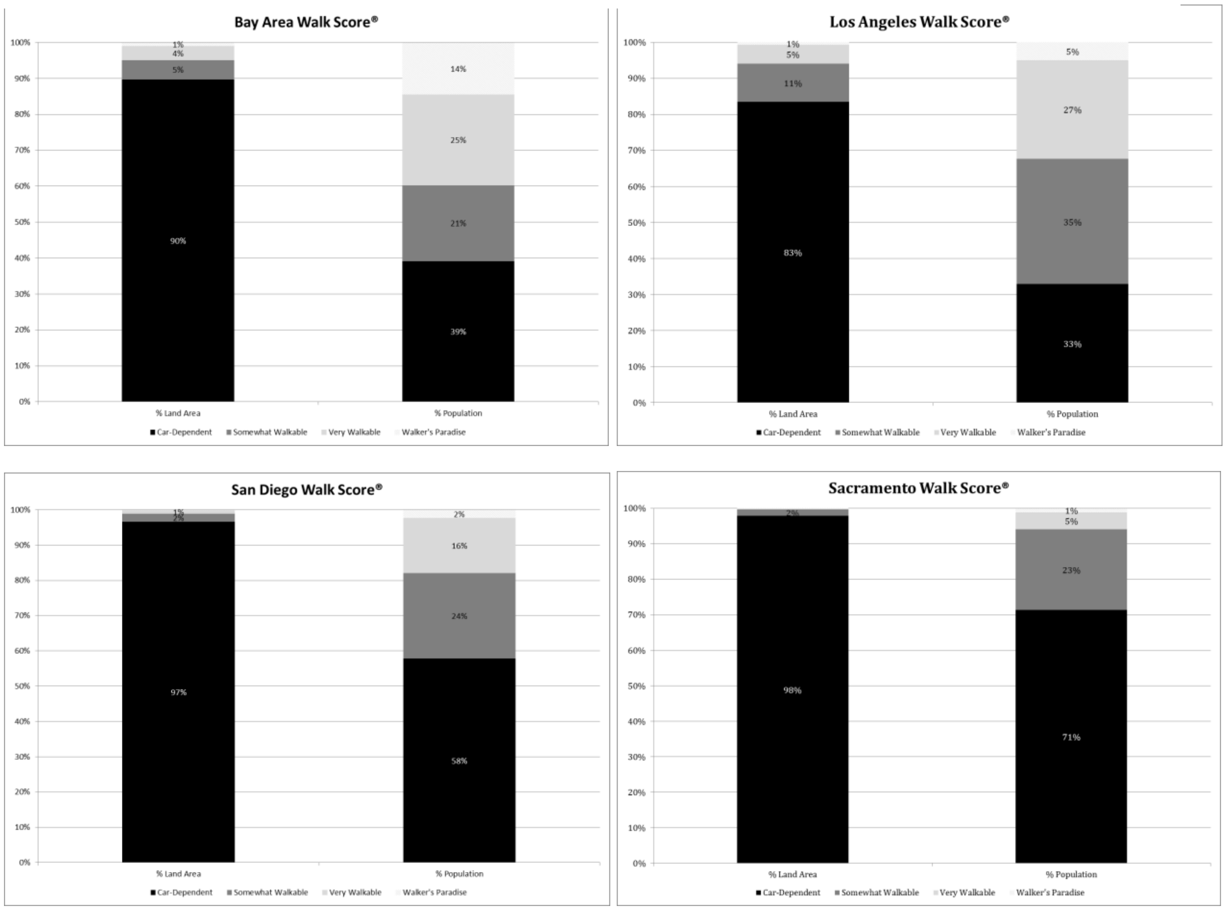
San Diego has an even higher percentage of car-dependent land area, over 96 percent, and nearly 60 percent of the population lives there. Another quarter of residents live in areas characterized as somewhat walkable. Thus, less than 20 percent of residents live in very walkable or walker's paradise bloc groups, which together constitute less than 1 percent of all land area.

Finally, in Sacramento, more than 97 percent of block groups are car-dependent and more than 70 percent of the population lives there. Just over a fifth of the population lives in somewhat walkable block groups, comprising less than two percent of the total land area. Finally, very walkable or walker's paradise block groups comprise 0.38 percent of total land area. These walking neighborhoods are home to roughly 6 percent of the population.

Table 21. Walk Score® Composition by MSA, Percent Land Area and Percent Population

Walk Score®	# Block Groups	Total Land Area	Total Population	% Land Area	% Population
Bay Area	**2,897**	**6,416,526,167**	**4,913,210**	**100%**	**100%**
Car-Dependent	1,119	5,760,114,797	1,923,409	90%	39%
Somewhat Walkable	614	340,557,969	1,040,299	5%	21%
Very Walkable	755	252,082,672	1,239,589	4%	25%
Walker's Paradise	409	63,770,729	709,913	1%	14%
Los Angeles	**8,241**	**12,555,094,931**	**14,220,824**	**100%**	**100%**
Car-Dependent	2,646	10,476,113,194	4,675,974	83%	33%
Somewhat Walkable	2,909	1,338,539,507	4,935,269	11%	35%
Very Walkable	2,292	657,366,041	3,901,446	5%	27%
Walker's Paradise	394	83,076,189	708,135	1%	5%
Sacramento	**1,370**	**13,194,448,617**	**2,358,391**	**100%**	**100%**
Car-Dependent	975	12,911,005,317	1,682,986	98%	71%
Somewhat Walkable	308	232,869,381	533,876	2%	23%
Very Walkable	70	44,755,195	114,120	0.3%	5%
Walker's Paradise	17	5,818,724	27,409	0.04%	1%
San Diego	**1,794**	**10,895,213,672**	**3,081,324**	**100%**	**100%**
Car-Dependent	1,018	10,527,680,038	1,782,051	97%	58%
Somewhat Walkable	441	244,465,775	747,261	2%	24%
Very Walkable	292	106,125,665	481,651	1%	16%
Walker's Paradise	43	16,942,194	70,361	0.2%	2%
Grand Total	*14,302*	*43,061,283,387*	*24,573,749*		

Figure 32. Distribution of land use and population by Walk Score® categories and by study region



Note: the bars are ordered from darkest (car-dependent) to lightest (walker's paradise)

Figure 33. Walkable land area by county

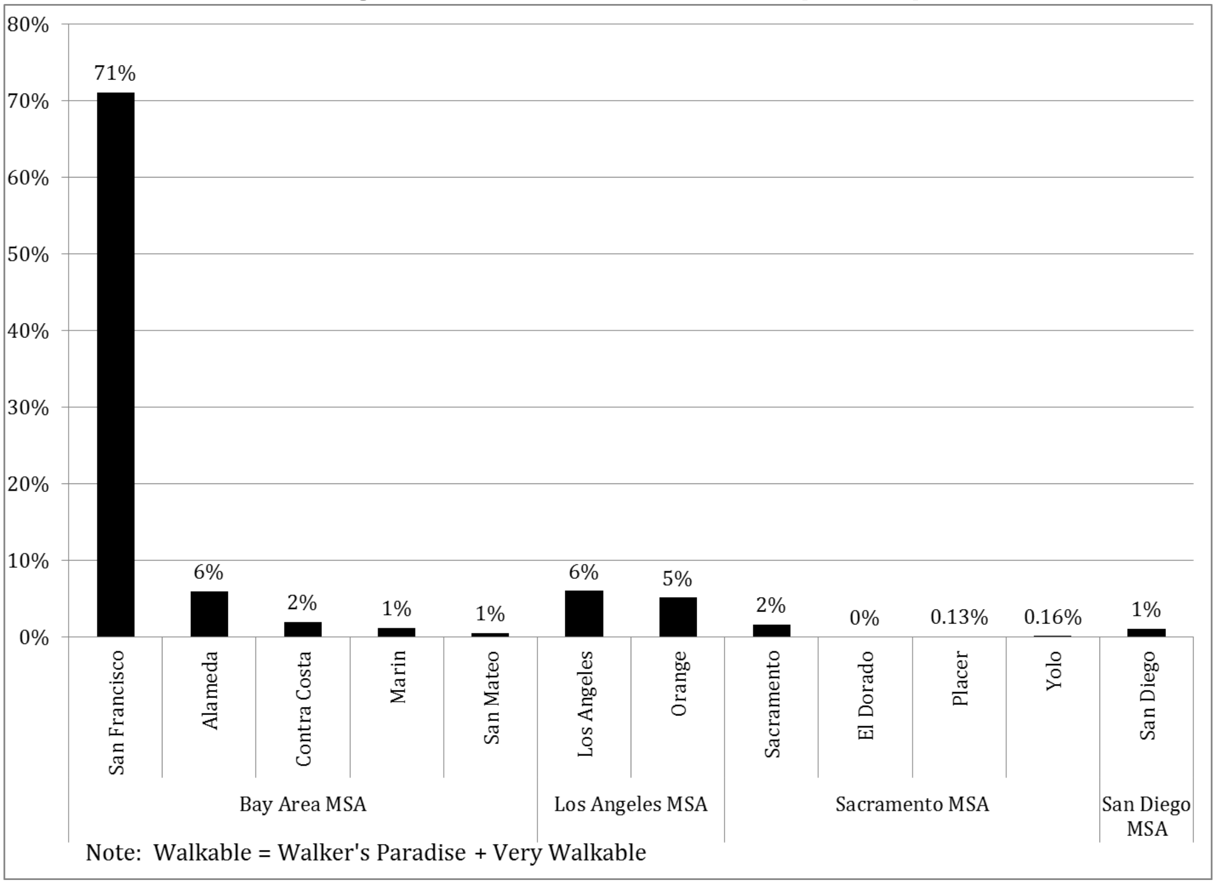
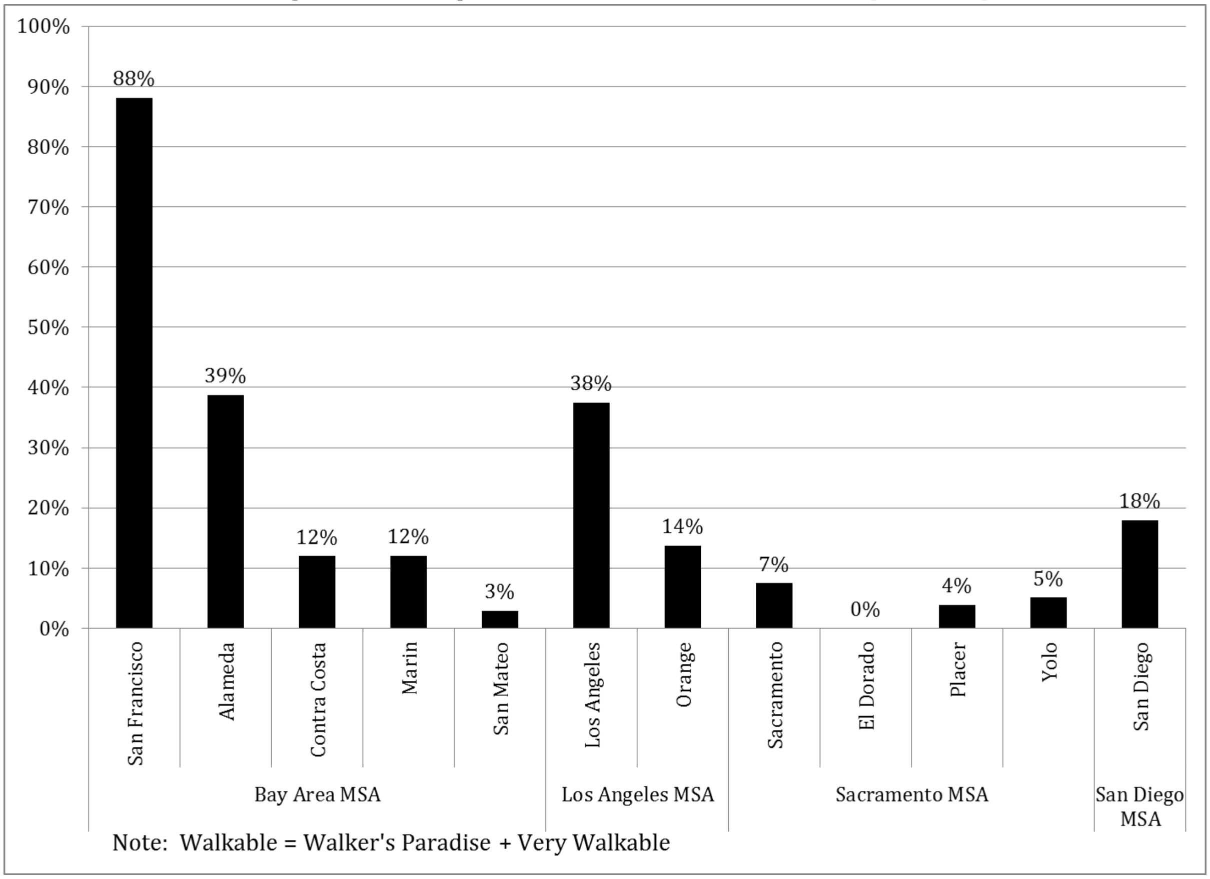


Figure 34. Population in walkable areas by county



Neighborhood typology

Descriptions of the development of the neighborhood types are included in Blumenberg et al. (2015) and Voulgaris et al. (forthcoming). They were constructed using data from three sources, which were applied to census tracts across the U.S.: (1) data taken directly from the Environmental Protection Agency (EPA) Smart Location Database, (2) data derived from the EPA Smart Location Database, and (3) 2010 Decennial United States Census data. The variables used in their factor analysis and their sources are summarized in Table 22. The five factors created from the larger set of 20 variables generally indicate the degrees to which a neighborhood is (1) dense, (2) diverse, (3) transient, (4) established, and (5) accessible.

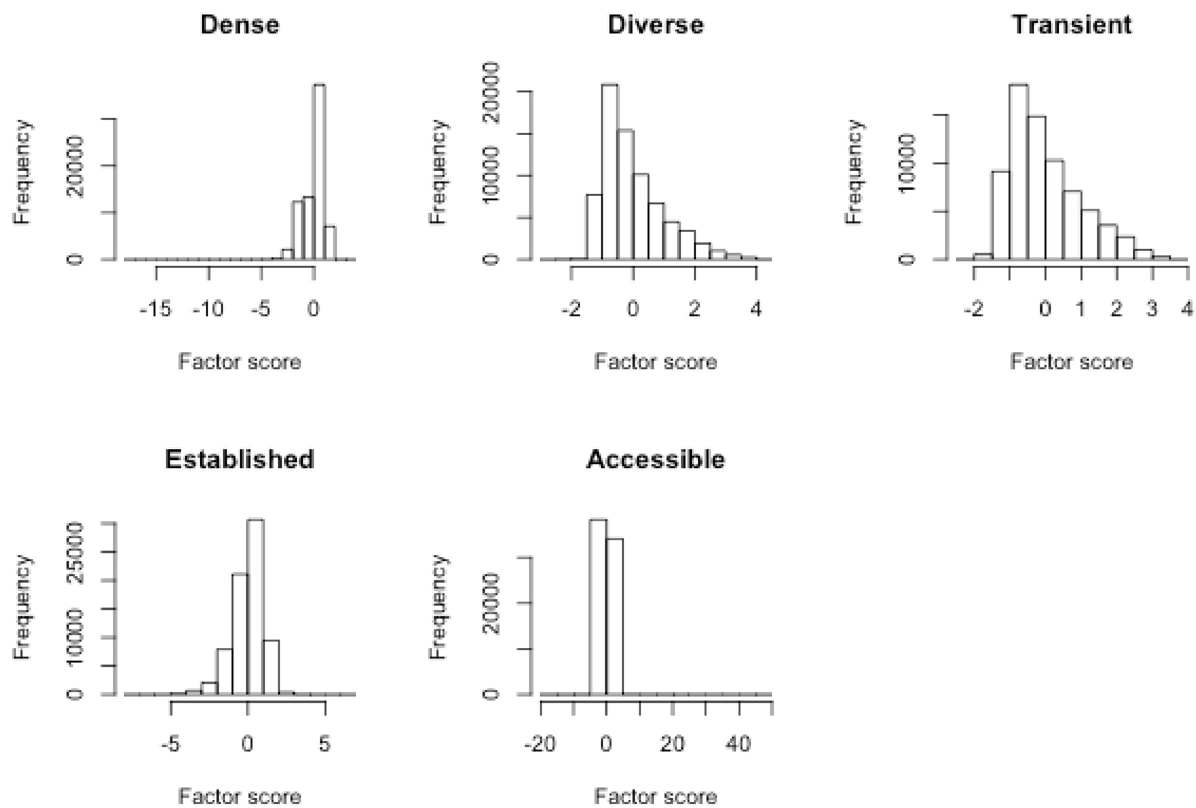
The distribution of each factor among the census tracts throughout the United States is shown in Figure 35. The distribution of the density variables across all census tracts is highly asymmetric, since a small number of tracts are extremely dense, relative to most of the country. Thus, the two factors that are most closely related to the density variables –density and diversity– have distributions with very long tails.

Table 22. Variables included in neighborhood classification analysis

Variable description	Variable name	Source
Number of jobs within a 45-minute drive	Job access	(1)
Share of total CBSA employment	Job share	(2)
Percent of total activity represented by employment	Percent jobs	(2)
Percent of total activity represented by office employment	Percent office	(2)
Percent of total activity represented by retail employment	Percent retail	(2)
Jobs-housing balance*	Job-housing balance	(2)
Housing density (log-transformed)	Housing density	(2)
Employment density (log-transformed)	Job density	(2)
Activity density (homes + jobs per acre) (log-transformed)	Activity density	(2)
Total road network density (log-transformed)	Road density	(2)
Pedestrian-oriented road network density (log transformed)	Pedestrian density	(2)
Car-oriented road network density (log-transformed)	Car network density	(2)
Intersection density (log-transformed)	Intersection density	(2)
Transit service density index (log-transformed)	Transit supply index	(2)
Share of homes that are single-family homes	Percent SFR	(3)
Share of occupied homes that are rentals	Percent rented	(3)
Share of occupied homes currently occupied for < 5 years	Short-term homes	(3)
Share of occupied homes currently occupied for > 20 years	Long-term homes	(3)
Share of homes less than ten years old	New homes	(3)
Share of homes more than forty years old	Old homes	(3)

Sources:
(1) EPA Smart Location Database
(2) Derived from the EPA Smart Location Database
(3) 2010 Decennial United States Census
Notes:
* This value is computed as 1 - 2|(Percent jobs – 0.5)|. A jobs-housing balance value of 1 indicates that there are equal numbers of homes and jobs. A value of 0 indicates that there are either no jobs or no homes in the tract.

Figure 35. Distribution of factor scores between census tracts



The authors use standardized factor scores for each census tract to conduct the cluster analysis and identify seven distinct neighborhood types: Rural, New development, Patchwork, Established suburbs, Urban residential, Old urban, and Mixed-use.

Table 23 shows how the seven neighborhood types vary in terms of each of the selected built environment characteristics.

Figure 36 shows how the factor scores vary among neighborhood types. The Patchwork and Mixed-use neighborhood types, for example, have similar high scores on the jobs-housing balance index; however, the housing density is much higher in Mixed-use neighborhoods than in Patchwork neighborhoods. Likewise, the age of the housing in Old Urban neighborhoods is similar to that in Established Suburbs, but the housing density in Old Urban neighborhoods is nearly seven times that of Established Suburbs.

Table 23. Average built environment characteristics by neighborhood type

	Homes per acre	Jobs-housing balance	Percent rental homes	Percent of homes > 40 years old	Jobs within a 45-minute drive (in thousands)	Transit supply index
All Neighborhoods	3.5	0.4	34%	46%	118	0.5
Rural	0.1	0.3	19%	42%	14	0.0
New development	1.4	0.2	19%	17%	68	0.0
Patchwork	1.7	0.7	35%	46%	94	0.1
Established suburbs	4.1	0.3	25%	74%	186	0.6
Residential urban	5.9	0.3	58%	56%	147	0.8
Old urban	27.5	0.3	76%	74%	533	4.2
Mixed-use	5.2	0.7	65%	49%	181	1.1

Figure 36. Variation in factor scores within and among neighborhood types

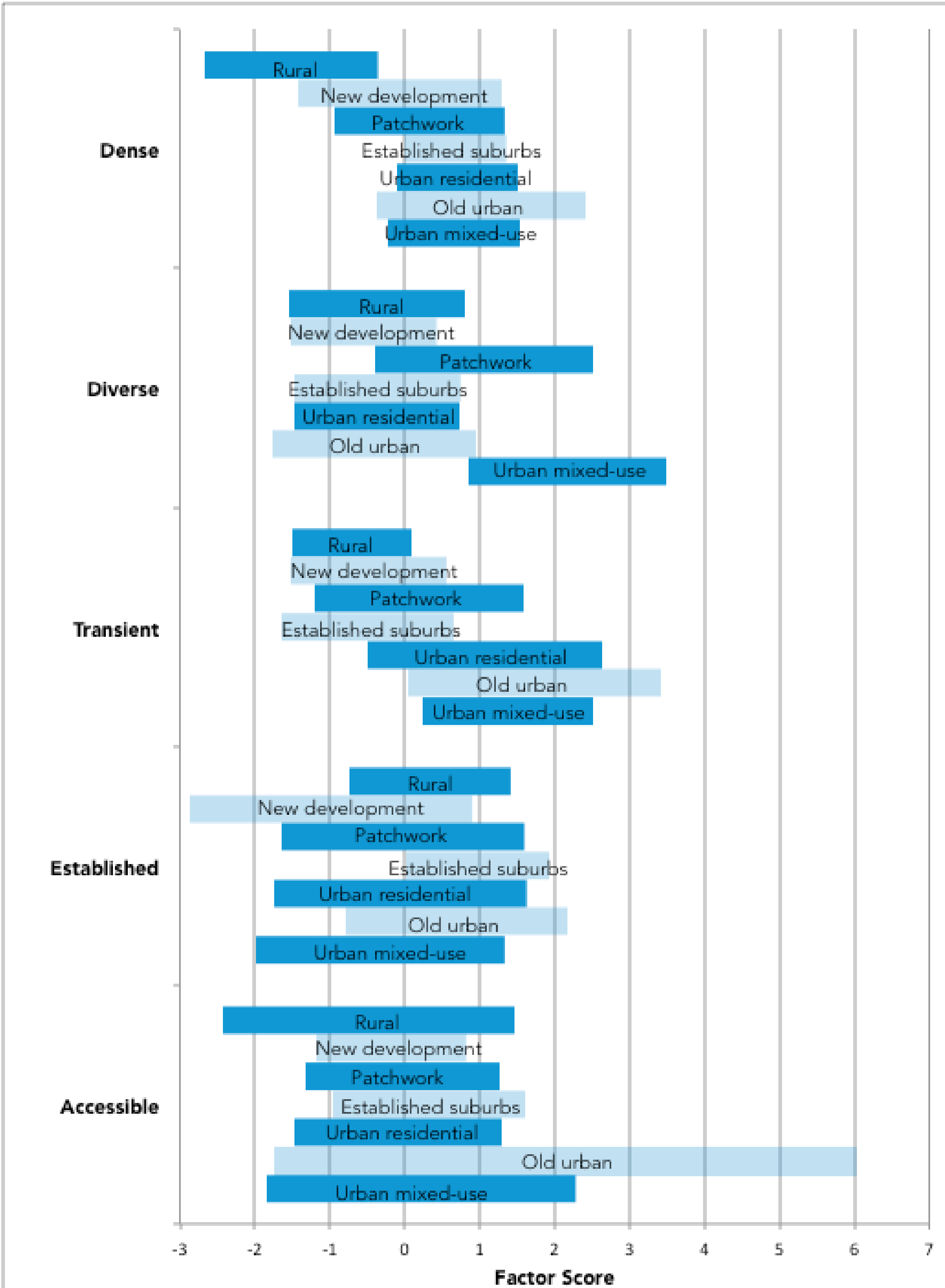
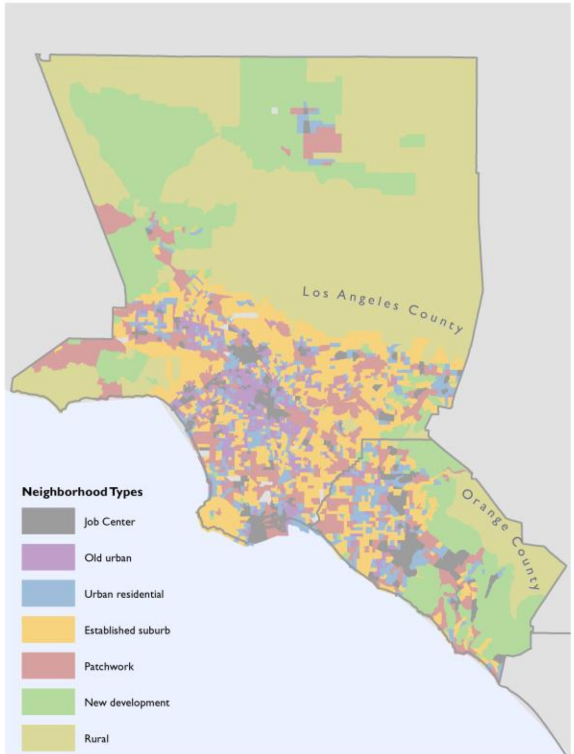


Figure 37. Characteristic images of each neighborhood type

Source: Google Earth, Google Maps

Although neighborhoods are not homogenous even within each type, Figure 37 illustrates each neighborhood type in terms of a characteristic image. These images give an overall sense of the qualitative differences among neighborhoods types. Map 4 illustrates the spatial arrangement of the neighborhood types in Los Angeles.

Map 4. Example: Neighborhood types in the Los Angeles region



While all of the cities shown above have a cluster of Mixed-use neighborhoods at the city center, this neighborhood type is not confined to downtowns. There are also mixed-use neighborhoods in commercial centers located closer to the edges of each city. Likewise, there are several Rural neighborhoods surrounded on all sides by Established Suburban neighborhoods or even adjacent to Urban neighborhoods. Nevertheless, moving from the center of each city to the outskirts, there is a distinct, if varied, progression from Mixed-use to Old Urban to Urban Residential to Established Suburb to Patchwork to New Development to Rural.

Figure 38 shows how the census tracts in each MSA in our study area are distributed among the seven neighborhood types, and Figure 39 shows how walking mode shares differ by neighborhood type.

Figure 38. Share of census tracts in each neighborhood type by MSA

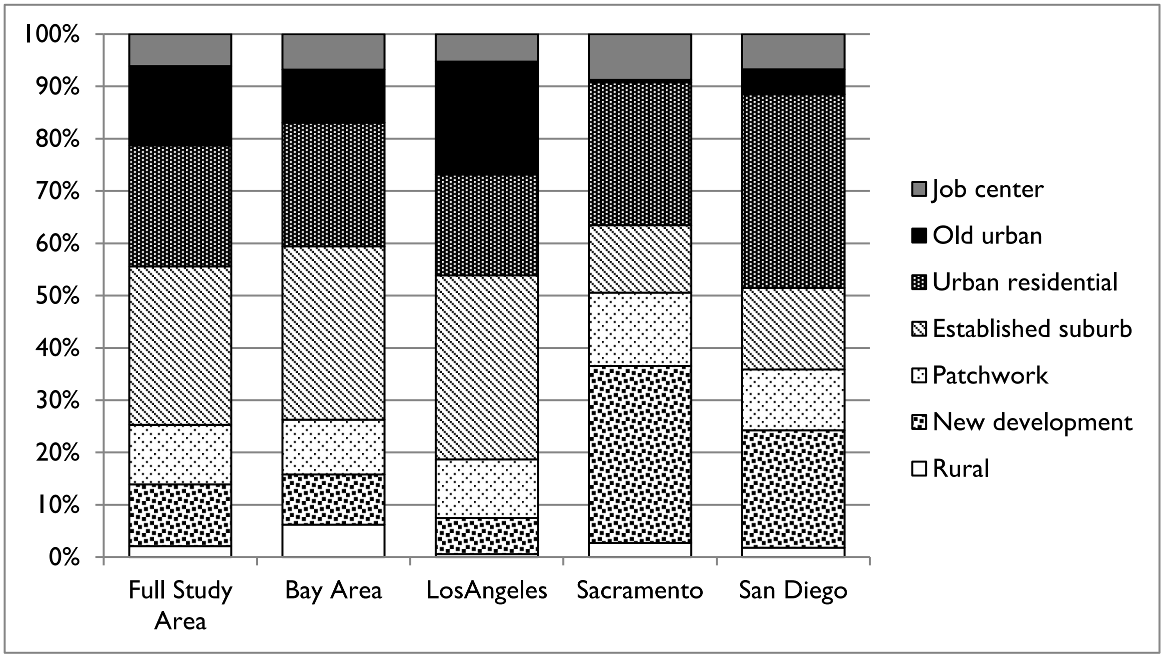
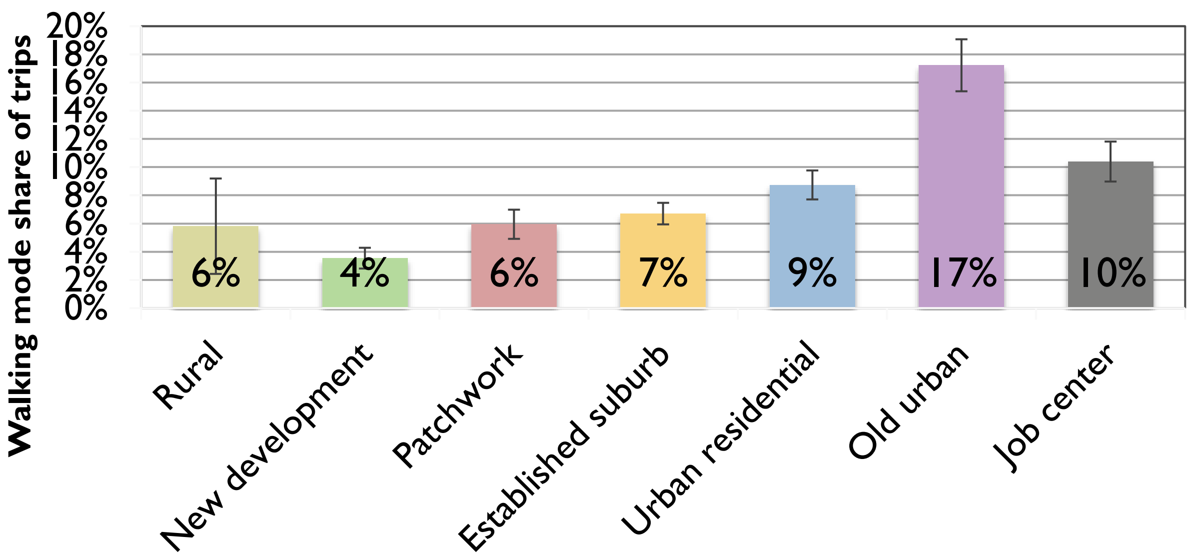


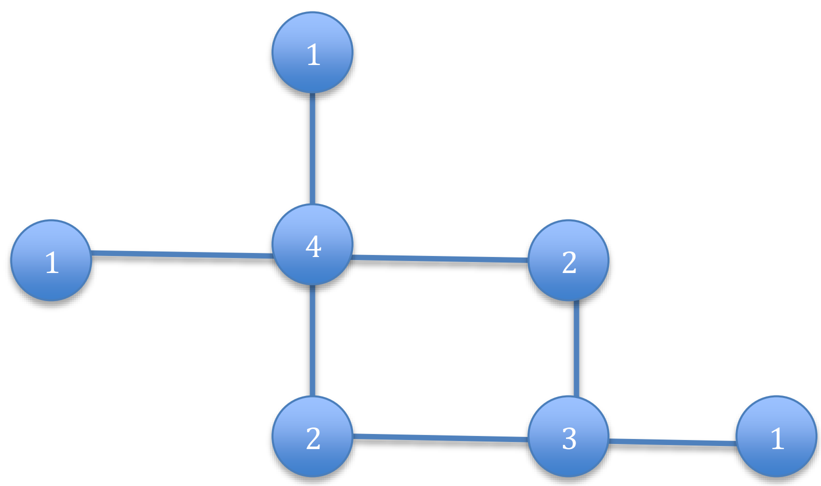
Figure 39. Walking mode shares by neighborhood type



Nodal degree

Average nodal degree is a measure of street connectivity. Nodal degree is the number of streets that join at an average intersection. Average nodal degree is simply the average across all intersections within a geographic area (such as a census tract). For example, Figure 40 shows a simple street network with one four-legged intersection (nodal degree = 4), one three-legged intersection (nodal degree =3), two two-legged intersections (nodal degree = 2), and three dead ends (nodal degree = 1). The average nodal degree for this simple network would be the average of the nodal degree for each individual intersection: (1 + 1 + 4 + 2 + 2 + 3 + 1) / 7 which is equal to two.

Figure 40. Illustration of nodal degree



Appendix D. Walk Score® by county

The following analysis considers Walk Score® across the 12 counties included in our study area. San Francisco County has the lowest car-dependent land area, 17.73 percent, and the least percentage of the population living there, 3.74 percent. The remaining 11 counties all have more than 75 percent car-dependent land area. San Diego, Contra Costa, Marin, Sacramento, El Dorado, Placer and Yolo Counties exceed 90 percent. El Dorado County leads with 99.77 percent; more than 93 percent of the county's population resides there.

In Los Angeles County, nearly a third of residents live in car dependent, somewhat walkable, or very walkable areas. Somewhat walkable areas surpass the other two categories just slightly with 33.91 percent of the population, despite accounting for less than nine percent of the county's total land area. Orange County has the highest percentage of somewhat walkable land area, 19.38 percent, and 37.60 percent of residents live there.

Only a few counties have more than 25 percent very walkable land areas. These include Alameda, Los Angeles, San Francisco and San Mateo Counties.

Of the counties in our study, San Francisco County has the highest percentage of land area in "walker's paradise" neighborhoods, nearly 30 percent. The county with the second highest percentage highly walkable neighborhoods is Alameda county where one percent of the land area is located in "walker's paradise." Both of these counties fall within the Bay Area MSA which explains why this region has the highest total land area and population that falls within walkable neighborhoods. San Francisco differs from every other county by having more very walkable or walker's paradise land areas than somewhat walkable and car-dependent. In fact, 10 of the 12 counties analyzed have less than one percent walker's paradise land area. Two counties, El Dorado and Placer, have no walker's paradise neighborhoods whatsoever.

Table 24. Walk Score® distribution: Los Angeles county (Los Angeles MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	1,764	8,930,366,658	3,194,699	84.97%	28.57%
Somewhat Walkable	2,226	941,764,707	3,792,021	8.96%	33.91%
Very Walkable	2,046	556,019,881	3,504,550	5.29%	31.34%
Walker's Paradise	383	79,199,698	688,773	0.75%	6.16%
Grand Total	6,422	10,510,356,737	11,183,936	100.00%	100.00%

Table 25. Walk Score® distribution: Orange county (Los Angeles MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	882	1,545,746,536	1,481,275	75.49%	48.71%
Somewhat Walkable	683	396,774,800	1,143,248	19.38%	37.60%
Very Walkable	246	101,346,160	396,896	4.95%	13.05%
Walker's Paradise	11	3,876,491	19,362	0.19%	0.64%
Grand Total	1,823	2,047,743,987	3,040,781	100.00%	100.00%

Table 26. Walk Score® distribution: San Diego county (San Diego MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	1,018	10,527,680,038	1,782,051	96.63%	57.83%
Somewhat Walkable	441	244,465,775	747,261	2.24%	24.25%
Very Walkable	292	106,125,665	481,651	0.97%	15.63%
Walker's Paradise	43	16,942,194	70,361	0.16%	2.28%
Grand Total	1,794	10,895,213,672	3,081,324	100.00%	100.00%

Table 27. Walk Score® distribution: San Francisco county (Bay Area MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	17	21,459,825	36,602	17.73%	3.74%
Somewhat Walkable	49	13,474,656	79,707	11.13%	8.15%
Very Walkable	215	50,310,166	341,174	41.57%	34.87%
Walker's Paradise	298	35,786,228	521,068	29.57%	53.25%
Grand Total	579	121,030,875	978,551	100.00%	100.00%

Table 28. Walk Score® distribution: Alameda county (Bay Area MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	359	1,669,020,681	630,104	87.20%	35.25%
Somewhat Walkable	274	131,038,588	465,061	6.85%	26.02%
Very Walkable	324	94,852,538	536,186	4.96%	30.00%
Walker's Paradise	89	19,133,207	156,214	1.00%	8.74%
Grand Total	1,046	1,914,045,014	1,787,565	100%	100%

Table 29. Walk Score® distribution: Contra Costa county (Bay Area MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	434	1,754,125,281	732,430	93.71%	68.67%
Somewhat Walkable	125	80,932,814	206,591	4.32%	19.37%
Very Walkable	73	35,249,102	121,774	1.88%	11.42%
Walker's Paradise	4	1,586,764	5,805	0.08%	0.54%
Unmarked	1	-	-	0.00%	0.00%
Grand Total	637	1,871,893,961	1,066,600	100%	100%

Table 30. Walk Score® distribution: Marin county (Bay Area MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	117	1,307,922,725	200,813	97.02%	69.14%
Somewhat Walkable	34	23,737,101	54,585	1.76%	18.79%
Very Walkable	21	15,570,108	31,155	1.16%	10.73%
Walker's Paradise	2	811,412	3,893	0.06%	1.34%
Grand Total	174	1,348,041,346	290,446	100%	100%

Table 31. Walk Score® distribution: San Mateo county (Bay Area MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	192	1,007,586,285	323,460	86.75%	40.94%
Somewhat Walkable	132	91,374,810	234,355	7.87%	29.66%
Very Walkable	122	56,100,758	209,300	4.83%	26.49%
Walker's Paradise	16	6,453,118	22,933	0.56%	2.90%
Unmarked	1	-	-	0.00%	0.00%
Grand Total	463	1,161,514,971	790,048	100%	100%

Table 32. Walk Score® distribution: Sacramento county (Sacramento MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	600	2,310,509,005	1,036,949	92.45%	66.41%
Somewhat Walkable	240	147,224,630	408,253	5.89%	26.15%
Very Walkable	56	36,122,756	90,156	1.45%	5.77%
Walker's Paradise	16	5,320,291	26,011	0.21%	1.67%
Grand Total	912	2,499,176,682	1,561,369	100%	100%

Table 33. Walk Score® distribution: El Dorado county (Sacramento MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	116	4,413,340,873	197,849	99.77%	93.93%
Somewhat Walkable	8	10,101,737	12,779	0.23%	6.07%
Very Walkable	0	0	0	0%	0%
Walker's Paradise	0	0	0	0%	0%
Grand Total	125	4,423,442,610	210,628	100%	100%

Table 34. Walk Score® distribution: Placer county (Sacramento MSA)

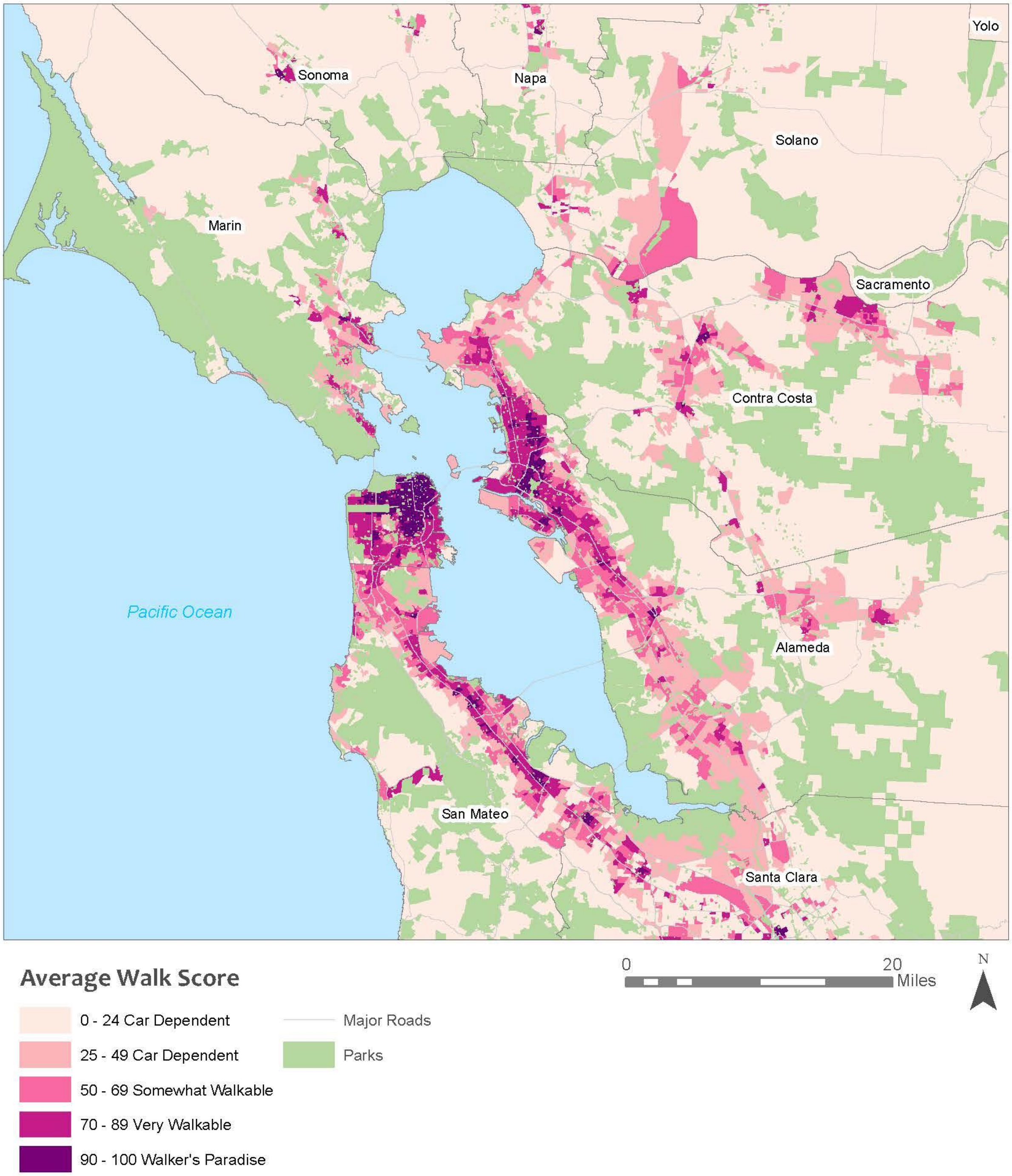
Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	178	3,600,311,201	312,130	98.81%	82.20%
Somewhat Walkable	27	38,426,587	52,718	1.05%	13.88%
Very Walkable	7	4,898,811	14,886	0.13%	3.92%
Walker's Paradise	0	0	0	0%	0%
Grand Total	213	3,643,636,599	379,734	100%	100%

Table 35. Walk Score® distribution: Yolo county (Sacramento MSA)

Walk Score®	# Census Tracts	Total Land Area	Total Population	% Land Area	% Population
Car-Dependent	81	2,586,844,238	136,058	98.43%	65.84%
Somewhat Walkable	33	37,116,427	60,126	1.41%	29.09%
Very Walkable	7	3,733,628	9,078	0.14%	4.39%
Walker's Paradise	1	498,433	1,398	0.02%	0.68%
Grand Total	122	2,628,192,726	206,660	100%	100%

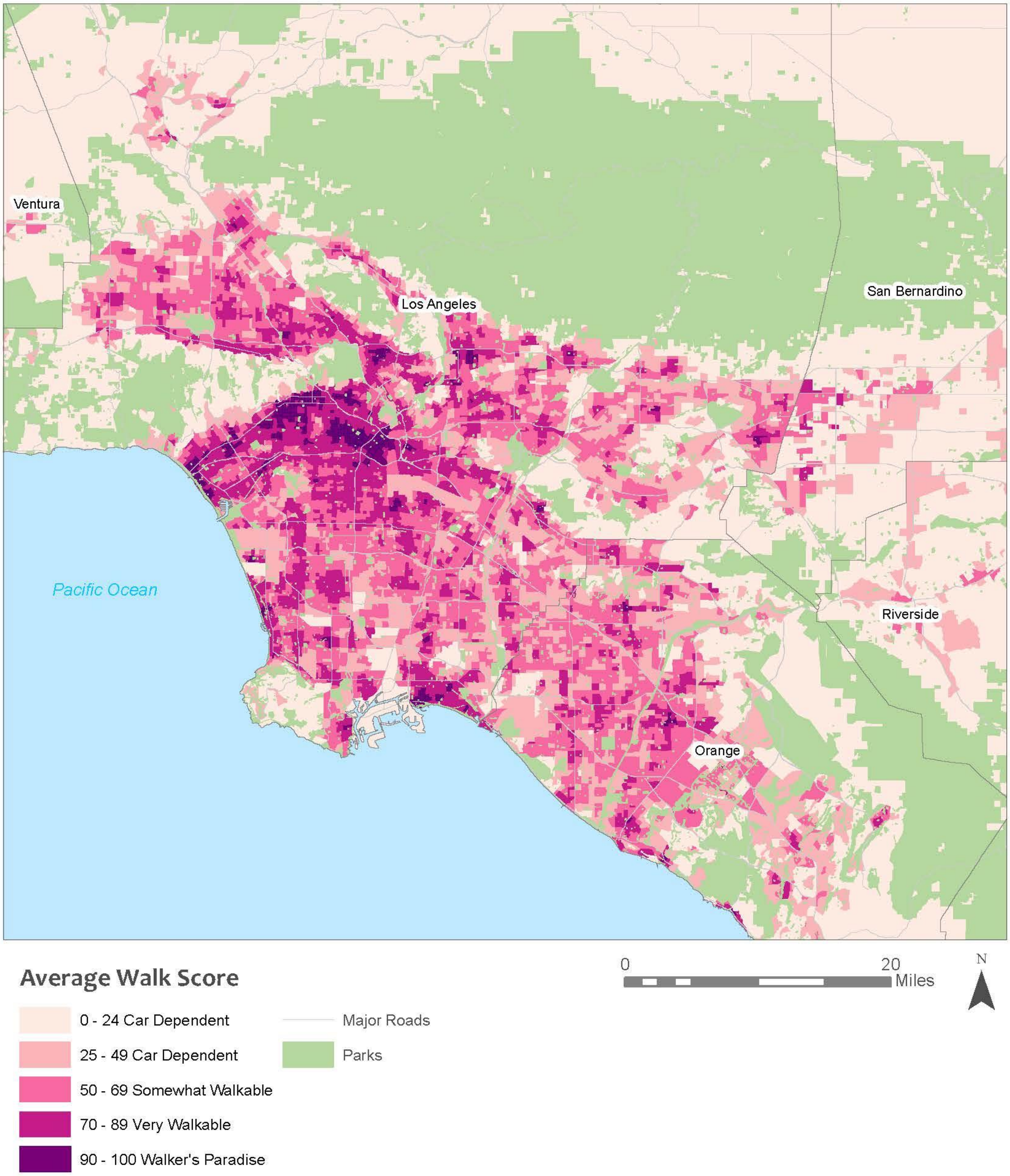
Appendix E. Walk Score® by metropolitan region

Map 5. Bay Area Walk Score®



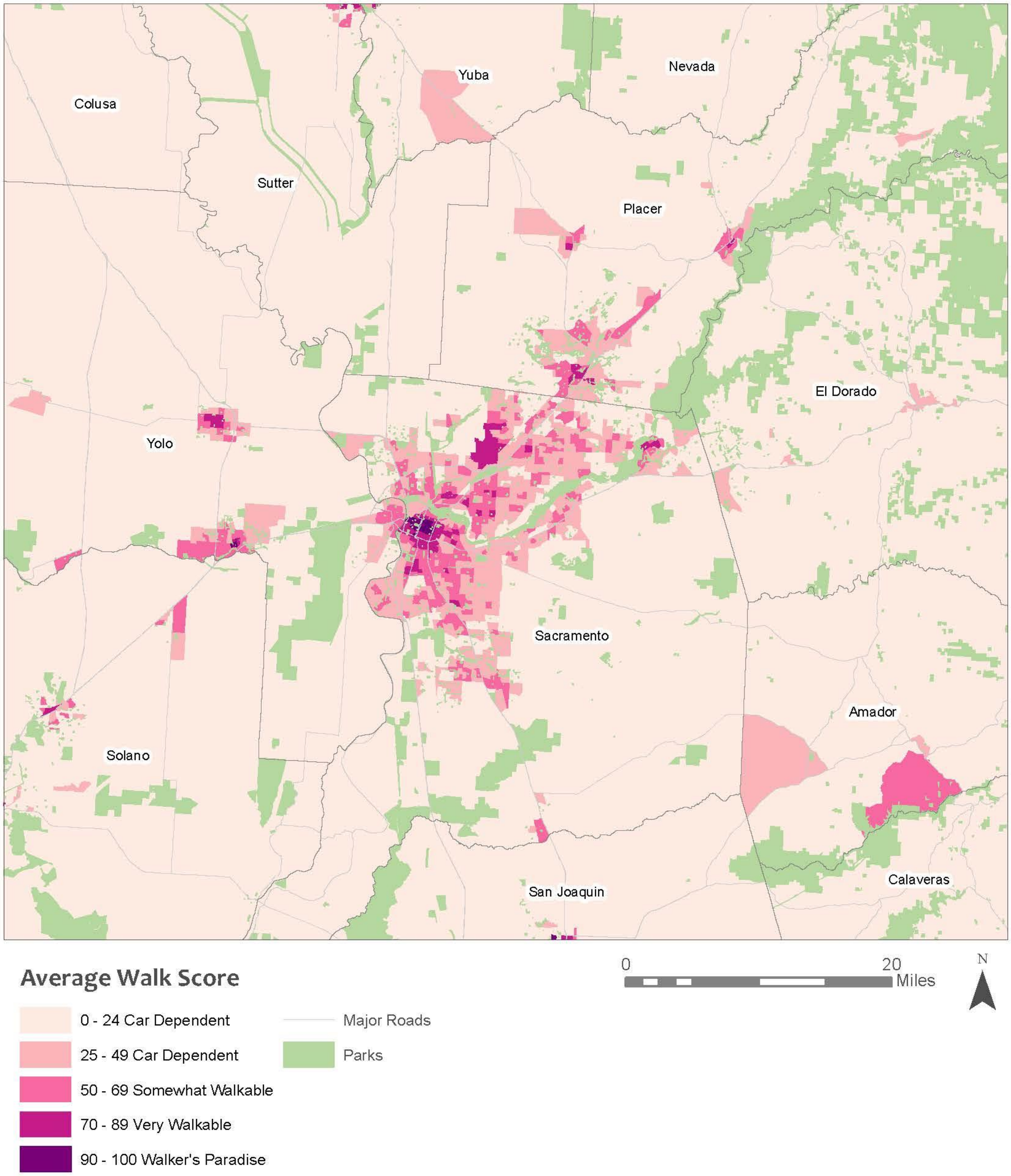
Classified Manually by Walk Score

Map 6. Los Angeles Walk Score®



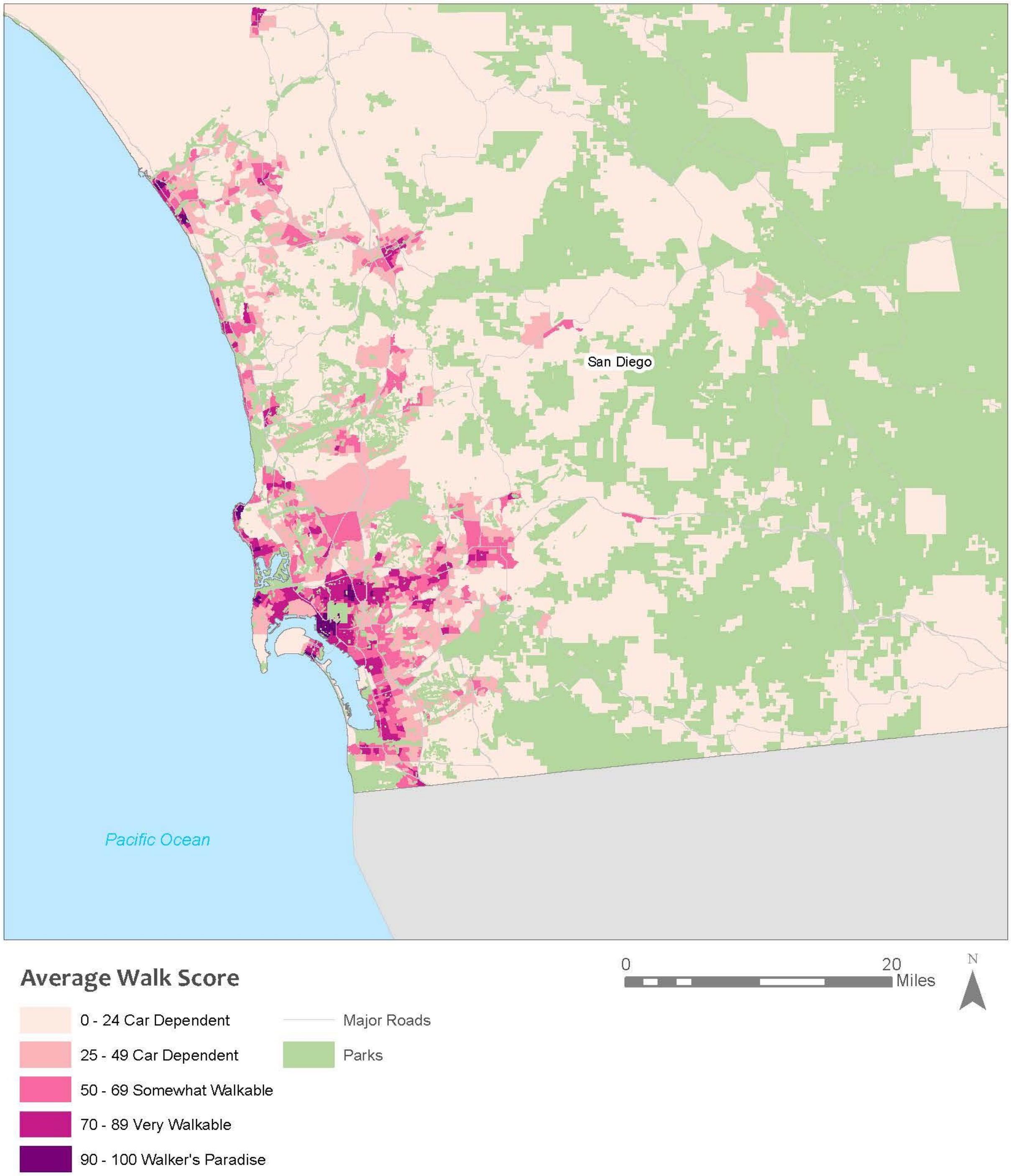
Classified Manually by Walk Score

Map 7. Sacramento Walk Score®



Classified Manually by Walk Score

Map 8. San Diego Walk Score®



Classified Manually by Walk Score

Appendix F. Interview protocol

1. Walk me through how your agency completes your regional travel modeling.
   a. Where do you get the data about the trips?
   b. What modes are included?

2. Are the inputs or outputs validated? If so, how?

3. What is the purpose of conducting these regional travel demand models?

4. What are the implications of these modeling efforts, after they are calculated, how are they used by your agency?

5. To what extent do other agencies in the region make use of these results?

6. What changes, if any, have been made to your modeling approach in the last ten years or so?

7. How often do you inventory regional land use/built environment changes that may have an effect on travel? How are these land use changes incorporated into the travel demand modelling process?

8. How does your modeling process account for short trips and/or trips that begin and end within the same traffic analysis zone?

9. Thinking about different types of trips in terms of length, purpose, and mode, which types of trips do you believe the model is best able to predict, and which types do you believe it is least able to predict? At what point might this type of bias become a problem? How might you correct for this kind of bias if it were to become a problem?

10. How does the model account for multi-modal trips, for example those in which someone walks, bikes, or drives to a transit stop or station, or walks from a remote parking space to their final destination?

11. Based on your own personal judgment, what is your best guess for the proportion of unlinked trips in your region are walk trips? What about transit trips?