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Mode Share Changes in California: An Exploratory Analysis of Factors Affecting Decreases in Walking, Biking and Transit Use from 2012 to 2017

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Mode Share Changes in California: An Exploratory Analysis of Factors Affecting Decreases in Walking, Biking and Transit Use from 2012 to 2017

November 2023

A White Paper from the National Center for Sustainable Transportation

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16. Abstract
This study explores the factors associated with observed changes in transportation mode shares over the period from 2012 to 2017 (corresponding with the period between the two most recent household travel surveys conducted in California). In contrast with the goals of the California Department of Transportation and the State Transportation agency, walking, biking, and using transit all decreased during this period, and driving and the use of personal vehicles increased. There are a number of factors typically associated with transportation mode choices, including socio-demographics, attitudes, life stages, land use and infrastructure availability. Further, large scale events may also have an effect on travel trends; for example, the Great Recession may have impacted individuals' ability to own a personal vehicle and therefore increased the use of alternative means of transportation during the years leading up to our survey period. Similarly, the 2013 passage of legislation allowing for non-citizens to obtain a driver's license in the state of California, may have impacted mode shares over the study period. This paper compares these and other factors impacting mode shares in 2012 and in 2017 to answer part of the question about why we see this decrease in the use of active modes over this period and what types of planning, programs, and policy actions may help to reverse this trend and get California back on track to increase walking, biking and the use of public transit.

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Mode Share Changes in California: An Exploratory Analysis of Factors Affecting Decreases in Walking, Biking and Transit Use from 2012 to 2017

EXECUTIVE SUMMARY

This study explores factors related to the changes in mode shares in California over the period from 2012 to 2017—corresponding with the most recent statewide household travel surveys; the 2012 California Household Travel Survey (CHTS) and the 2017 National Household Travel Survey (NHTS) which included a large California “Add on” sample.

This study builds on the earlier work of Pike and Handy (2021, and 2022) that examined methodological differences between the two surveys and found that there are no methodological differences that can alone, explain the decreases in walking, biking, and transit use over the study period. Thus, the current study examines other (non-methodological) factors that may account for these changes.

In particular we look at changes in the behaviors within demographic groups, for example, we observed greater decreases in walking and biking among Hispanic Californians than others. We also discuss these within demographic changes with respect to changes in the overall population of California; in addition to Hispanic individuals making different choices, the proportion of the population that is Hispanic was greater in 2017 than in 2012. These two types of changes may be important for the mode share changes.

Overall, the models tend to show expected outcomes related to trip mode with respect to a number of individual and household characteristics for trip mode in each year. There are few differences between the models, but we take a closer look at the descriptive and demographic changes that might be leading to the changes in shares, even if there is not a clear model outcome that suggests major differences. Namely, income and Hispanic status are different in terms of mode shares, and vehicle ownership has changed for these groups over the study period and may partially explain the shifts in mode share. To analyze this concept more formally, we use interaction terms in the models to determine if vehicle ownership has different impacts depending on an individual being Hispanic and/or across income levels.

Introduction

There was a decline in the use of biking, walking, and using transit, in the state of California during the period from 2012 to 2017 (Pike and Handy 2021). This period corresponds to the times the most recent California Household Travel Survey (CHTS) and National Household Travel Survey (NHTS) were conducted, respectively. This decline also coincides with a period of time (2015 to 2020) when the California State Department of Transportation and the State Transportation Agency had the goal of tripling walking and doubling biking and transit use in their long-range strategic plan with the 2012 CHTS results as a baseline. (California Department of Transportation 2015). This study explores the factors associated with these declines and employs survey data collected through the 2012 CHTS and the 2017 NHTS to explore the effects of sociodemographic, and other factors in these changes.

We investigate these changes with two pathways in mind. First, have changes made within groups. For example, are women in 2017 making different choices than in 2012, and to an extent great enough to contribute to the overall changes in mode shares in the state over this time? Alternatively, are the decisions made within groups stable over time, but has the share of women (for example) in the population grown such that their choices impact the overall mode shares to a greater extent in 2017 than in 2012? While gender is an unlikely candidate for either of these pathways, we do find that changes in mode share were more substantial among Hispanic individuals than others, and at the same time, Hispanic individuals made up a larger proportion of California's population in 2017 than in 2012 (Public Policy Institute of California, n.d.). These changes within the group along with the share of the population made up by this group together likely contribute to the overall shift in mode use away from active modes. Schouten et al. (2021) differentiate these impacts as *rate* and *composition* effects and note that when groups, such as the Hispanic population in California make up such a large segment of the population, changes within the group can affect overall mode shares in the state. At the same time, if the population share changes enough (even without shifts *within* the specific group), this alone could impact outcomes on the whole.

Changes along both of these pathways could be affected by external events or shocks, such as the Great Recession. The Great Recession of 2009 that some have suggested may have had impacts that extended up to 2012 (Beuhler 2020) directly or indirectly through gas prices, unemployment rates and or other economic processes. The Recession impacted employment and household income and indirectly impacted household vehicle numbers and likely the availability of funds for transportation expenses including fuel. This interplay between income, household vehicle ownership and population shifts likely contribute to the observed shifts in mode shares over the study period.

Using descriptive statistics, we enumerate changes in mode use among different groups and as they relate to individual, household, and trip characteristics. We also employ multinomial logistic regression models estimated for each survey, to identify differences in the effects of important factors in 2017 and 2012.

Background

Phase 1 of This Study

In earlier work, the authors examined the decreases in the use of walking, biking, and transit over the time period of interest here. We found that the declines in these modes were not attributable to differences between the two surveys and were likely the result of other factors (Pike and Handy 2021 and 2022). This study builds off of that work and uses the same data to identify factors that may have different impacts in 2012 than in 2017. The previous study covers the changes and offers some insight into the reasons that there are changes by examining whether changes are more prevalent among some groups, and whether having particular characteristics is more important to mode choices in 2012 than in 2017. Below we reproduce the table from that report, to show the magnitude of the changes found in the first study. The modes presented in this table are consolidated for consistency across the two surveys (a discussion of this consolidation is presented in Pike and Handy 2021). Standard errors and confidence errors were produced for 2017. This was not possible for 2012, but if we assume similar confidence intervals we can see where the changes are likely due to more than just random changes. This table shows that there are notable declines in transit use, biking and walking and an increase in the use pf private vehicles and hired vehicles. Certainly, the changes in taxi and hired vehicle use reflect the increased availability of ridehailing in 2017 than in 2012 (as the TNC concept was nascent in 2012 and much more widely available and used in 2017).

Table 1. Weighted Mode Shares for Consolidated Travel Modes (Reproduced from Pike and Handy 2021)

Grouped Modes (for Consistency)	Weighted Count 2012*	Weighted and Expanded Count 2017*	Standard Error 2017	Confidence Interval 2017 (as percent)	Weighted Share 2012	Weighted and Expanded Share 2017	Percent Change in Share from 2012 to 2017
Airplane	382.22	49934754.09	7869595.28	+/- 31%	0.10%	0.16%	60%
All local bus types	11333.97	664094446.1	53379947.60	+/- 16%	2.91%	2.09%	-28%
Amtrak; bus and comm rail	488.45	88589610.79	7809818.36	+/- 17%	0.13%	0.28%	115%
Bicycle	5943.11	427724099.4	25364963.18	+/- 12%	1.53%	1.34%	-12%
City-to-city bus	7.37	6405980.756	1758594.57	+/- 54%	0.00%	0.02%	0%
Ferry or boat	56.05	21749519.7	5523833.42	+/- 50%	0.01%	0.07%	600%
Metro, rapid, trolley	3830.83	259048386.3	12565597.76	+/- 10%	0.99%	0.81%	-18%
Motorcycle	873	83704147.59	20198827.09	+/- 47%	0.22%	0.26%	18%
Paratransit	258.27	35056481.67	11697823.71	+/- 65%	0.07%	0.11%	57%
Private shuttle bus	603.71	78035341.49	11112452.84	+/- 28%	0.16%	0.25%	56%
Private vehicle	297614.56	25454330265	202567922.00	+/- 2%	76.52%	79.97%	4%
Rental	606.76	44313791.24	8105122.16	+/- 36%	0.16%	0.14%	-13%
School bus	2400.33	212837711.1	24656886.63	+/- 23%	0.62%	0.67%	8%
Something Else	1248.08	107370506.7	13824083.38	+/- 25%	0.32%	0.33%	6%
Taxi or hired car	421.28	170656177.3	27394288.19	+/- 31%	0.11%	0.54%	391%
Walk	62879.18	4127847356	124691548.60	+/- 6%	16.17%	12.97%	-20%

*Counts are weighted and therefore not whole numbers. 2017 values are expanded, 2012 are not.
1. Weights applied here are contained in the data used for this analysis; new weights were not computed here. For details on the weighting procedures, see section 3. methodological differences.

Trends in Active Transportation Mode Use

A number of studies evaluate trends in walking, biking, and transit use, using the National Household Travel Survey. The NHTS was most recently conducted in 2001, 2009 and 2017. Some studies use only the NHTS data from 2001 and 2009, others incorporate the 2017 NHTS data. Le et al. (2019) show that there is a high point in walking and biking in 2009, when considering all three of these datasets (Le et al. 2019). The authors also explore the period from 2004 to 2016 and determine that bike and pedestrian counts increase over this time and using American Community Survey (ACS) data they find biking and walking level off (Le et al. 2019). It is possible that the higher active mode use in 2009 may be due to the Great Recession and related changes in income, employment, and the price of fuel; and that the slower or almost flat increase in biking and walking from 2001 to 2017 is a more reliable long-term trend (Beuhler et al. 2020).

Other studies have focused on specific locations and examined changes in mode use over time; in Southern California there was an increase in walking from 2001 to 2009 (Joh et al. 2015), and over the period from 2011 to 2015 bicycling in Seattle increased (Chen et al. 2017). A few key factors: higher levels of education, lower car ownership, and high-density neighborhoods are factors associated with increases in walking. In addition, walking and cycling were lower among 5–15-year-olds in 2017 than 2001 while walking and cycling increased among other groups (Buehler et al. 2020). Higher levels of biking were also associated with improved or better infrastructure, proximity to water bodies, and flatter topology (Chen et al. 2017). Population density, access to different modes of transportation, income and household size are also important factors for active mode use, when considering the 2017 NHTS on its own (Tribby and Tharp 2019). Barriers to bicycling more among the participants in the 2017 NHTS include safety and infrastructure needs, as perceived by participants (Porter et al. 2020).

Another factor that has impacted mode choice is the introduction of Transportation Network Companies (TNCs). TNCs have replaced the use of transit and other active modes at least to some extent (for example Metropolitan Area Planning Council 2018, Clewlow and Mishra 2017). In a related study, Erhardt et al. (2022) estimate that ridehailing led to decreases of as much as 10% in transit ridership in some areas.

Factors Affecting Mode Shares

In general, we expect factors known to impact biking and walking to be relevant in our study. Considering changes in California's population over time, we look at the percent of the population that is Hispanic. The proportion of the state's population that was white in 2000 was 47%, but this decreased to 37% by 2018. Meanwhile the Hispanic proportion increased from 33% to 39% over the same period (Public Policy Institute of California); the Hispanic population includes both immigrants and native-born Hispanic individuals. Immigrants (which includes some, though not all of the Hispanic population) are more likely to use modes other than driving (Tal and Handy 2010), however as individuals reside in the US for longer, they are more likely to shift to driving (Blumenberg 2009). The higher proportion of the Hispanic population, coupled with their potential to shift away from active modes over time, may be contributing to the overall changes in California's mode shares during the study period.

Shaheen et al. (2018) identify three distinct factors that may affect trends; period effects including things like shifts in demographics and important events, life stage effects that relate to changes in behavior for individuals as their life changes such as having kids, or having a higher earning job, and cohort effects or generational effects that signal that different generations may behave differently than other generations. Any of these changes might be contributing to the shifts in mode shares observed in California.

There is evidence that younger adults are waiting longer to get a driver's license; over the 31-year period from 1983 to 2014 there was an 18% drop in the number of 19-year-olds with a license (Schoettle and Sivak, 2016). Further, Libde et al (2021) show that older adults responding to the most recent NHTS may have different travel patterns than those in the same demographic group at earlier iterations of the NHTS. Older persons, defined as those over the age of 65 made up a larger proportion of the NHTS sample in 2017 (15.78%) than in 2001 (11.86%), and the overall share of trips made by this group is higher during this period; increasing from 10.06% to 14.98% (Libde et al. 2021). They also find that older people are less likely to use a car in 2017 than in 2001, though they may be more likely to make longer distance trips in 2017 than in 2001 (Lidbe et al. 2021). At the same time, older age groups are less likely to bike and walk, and when they do it is for shorter distances (Shaheen et al. 2018); older individuals may also be less likely to bike and walk for their commutes, even if they might have at younger ages.

At the other end of the age spectrum, McDonald et al. (2011) examine school travel over the period from 1995 to 2009, using three iterations of the NHTS. They find that the proportion of younger students being driven to school has steadily increased over this 25 year period, though driving and being driven has declined for high school students over the study period (McDonald et al. 2011).

In related work looking at cohort and age effects, results show that transit use is higher among teens and young adults (Brown et al. 2016). The authors examine the age effect vs. the cohort effect and find that transit use was not affected by cohort membership, though transit did decrease with age; older individuals use transit less than younger individuals both the previous day, and when considering transit use in the preceding month (Brown et al. 2016). However, some work accounting for a variety of factors in travel behavior changes found that the only one that seemed to actually matter is socio-demographics, even when including cohort and period effects (Da Silva et al. 2019).

While the trends noted here have been observed in various studies and overlap with the study period for this paper, here we look specifically at travel trends in the state of California, and we explore factors related to the period from 2012 to 2017, a slightly different period than many of the aforementioned studies; and corresponding to the most recent CHTS and NHTS.

Methods

This study builds on the work of Pike and Handy (2021) and explores the factors associated with the decline in the use of active modes in California over the period from 2012 to 2017. A comprehensive examination of the differences in survey methods found no substantial differences in the outcomes of interest would result from differences in methods between the two surveys (Pike and Handy 2021 and Pike and Handy 2022). Earlier work focused on trip mode share as the key metric of interest to explore changes in active mode use between 2012 and 2017.

Here, we build on those findings and examine the non-methodological factors that are likely to contribute or relate to the observed changes in mode shares. The focus remains on trip mode shares, as we are concerned with the overall change in mode use over the study period. We examine factors that are typically associated with transportation mode choice, and the changes in demographics in the state, as well as potential events or period effects that could have impacted mode shares over this time.

While there are a number of ways to evaluate increases or decreases in biking, walking, and transit (usual mode to work or school, any use of biking, trip mode choice, etc.) we focus here on trip mode shares as this provides a means to evaluate the overall trends in California's travel over the time period between these two household surveys. We explore key demographic and individual characteristics known to be related to mode choice, or that may have substantially changed in the state of California over the study period.

Sample and Weighting

The sampling and weighting processes used in the analysis of the NHTS and CHTS aim to produce representative statewide estimates of mode shares and other values, however there are some limitations to weighting. First, not every factor may be included, and some factors related to the built environment including land use classifications and physical infrastructure typically cannot be incorporated into weighting procedures. We apply the sample weights present in the publicly available CHTS and NHTS data in the calculation of descriptive statistics in order to assess whether any mode share changes have been greater within some groups than others.

However, in our multinomial logistic regression models, we do not apply weights to the sample. We do not use the full sample of the CHTS nor the NHTS in these model estimations and we do not have a representative sample, since we are looking at only a particular subset of modes.

Results

In this section we present results of exploratory analysis including descriptive statistics and multinomial logistic regression models.

Descriptive Statistics

This section on descriptive statistics considers the variables that may be important for explaining observed changes in trip mode share. The proportions shown in each of the following tables and figures were calculated using the entire sample of trips including transportation modes that are not shown, however we reduced the number of modes presented because the shares of some modes are extremely small, and any related changes are also fractions of a percent. We present the modes that have close to or greater than 1% of the mode share overall. This includes local bus, bike, metro/rapid transit/trolley, private vehicle, taxi/hired vehicle, and walk. All of the values presented in the descriptive statistics are weighted using the weights available in the public data.

First, we consider individual characteristics of the person making a trip. Whether the individual is Hispanic or not was explored in earlier work. In addition to this group making up a larger proportion of the California population in 2017 than in 2012, this group had a greater shift away from active modes and towards driving in the study period (Pike and Handy 2021). Table 1 is reproduced from Pike and Handy (2021) to show the relevant modes and the changes by Hispanic/non-Hispanic individuals. These results demonstrate that within group changes may be reflected in the overall shifts at the population level. We also note that as those groups increase or the proportion of the population made up of that group changes, it may have compounded impacts on mode shares. This result is also evident in other studies; Hispanic individuals made fewer transit trips in 2017 than in 2009 (Schouten et al. 2021).

Table 2. Weighted[1] Trip Mode Shares for Hispanic and Non-Hispanic Groups. (Reproduced from Pike and Handy 2021)

Trip Mode	Hispanic 2012		Hispanic 2017	
	count	**percent**	**count**	**percent**
All local bus types	6603.45	4.85%	973713.11	2.22%
Bicycle	1619.15	1.19%	350765.45	0.80%
Metro, rapid, trolley	1251.48	0.92%	148088.31	0.34%
Private vehicle	94176.25	69.13%	36491149.94	83.11%
Taxi or hired car	115.21	0.08%	211407.22	0.48%
Walk	29807.71	21.88%	4927647.82	11.22%
Trip Mode	**Not Hispanic 2012**		**Not Hispanic 2017**	
	count	**percent**	**count**	**percent**
All local bus types	4620.57	1.88%	1261009.29	1.65%
Bicycle	4262.52	1.73%	1156126.44	1.51%
Private vehicle	198145.38	80.45%	60769895.09	79.54%
Metro, rapid, trolley	2540.45	1.03%	682542.76	0.89%
Taxi or hired car	293.19	0.12%	563435.22	0.74%
Walk	32310.91	13.12%	10179916.74	13.32%

[1] The weighting was applied to this table in the original report and includes all of the transport modes thought they are not all shown in the table. Percentages do not add up to 100% because modes used by less than these shares are removed from the table.

Differences in mode shares by gender were examined in Pike and Handy (2021) and there are not many notable changes. The mode share for biking is slightly higher for both men and women in 2012 than in 2017. The decrease among males is slightly more than among females, and the reverse is true for walking—a little more of a drop for women as opposed to men. In both cases the group with the higher share to begin with decreases more; perhaps because there is more room for that to occur.

Table 3. Weighted[1] Trip Mode Shares by Gender. (Reproduced from Pike and Handy 2021)

Trip Mode	Female 2012		Female 2017	
	count	percent	count	percent
All local bus types	6511.72	3.13%	1261422.32	2.04%
Bicycle	1841.46	0.89%	431899.95	0.70%
Metro, rapid, trolley	1889.64	0.91%	343087.93	0.55%
Private vehicle	159593.25	76.73%	50535811.42	81.60%
Taxi or hired car	224.90	0.11%	375706.77	0.61%
Walk	35039.04	16.85%	7917158.75	12.78%
Trip Mode	**Male 2012**		**Male 2017**	
	count	**percent**	**count**	**percent**
All local bus types	4804.72	2.68%	979942.00	1.68%
Bicycle	4081.32	2.27%	1076308.98	1.84%
Metro, rapid, trolley	1920.64	1.07%	486991.60	0.83%
Private vehicle	136809.67	76.21%	46789994.79	80.06%
Taxi or hired car	189.01	0.11%	399135.67	0.68%
Walk	27713.39	15.44%	7189757.86	12.30%

[1] The weighting was applied to this table in the original report and includes all of the transport modes thought they are not all shown in the table. Percentages do not add up to 100% because modes used by less than these shares are removed from the table.

Next, we explore changes in mode shares with respect to having a driver's license. The two surveys did not have the same driver's license question; in 2012 the question asks whether the person has a driver's license, however in 2017 it asks whether they are a driver. The mode shares of those who report that they are a driver (or have a license) are quite similar between 2012 and 2017, however among those who are not drivers, the shares in 2017 are more skewed towards private vehicle. It is possible that the proportion of the population with a driver's license changed over the study period – in particular as a result of 2013 legislation that allows non-citizens to obtain a California driver's license. Below, we explore changes in driver's licensure as it relates to income, and Hispanic identity, to explore the possibility that the likelihood of having a driver's license changed for particular groups.

Table 4. Weighted[1] Trip Mode Share by Driver Status

Trip Mode	Mode Share with Driver's License 2012	Mode Share without Driver's License 2012	Mode Share of Drivers 2017	Mode Share of non-Drivers 2017
All local bus types	1.4%	13.5%	0.9%	5.4%
Bicycle	1.3%	2.2%	1.0%	2.3%
Metro, rapid, trolley	0.9%	2.3%	0.7%	0.7%
Private vehicle	84.4%	35.1%	84.8%	66.9%
Taxi or hired car	0.1%	0.2%	0.6%	0.9%
Walk	10.7%	44.1%	10.5%	20.0%

[1] Weights present in the publicly available data were applied to the full sample, though not all modes are presented here; therefore, percentages do not add up to 100%.

Next, turning to trip mode shares and education; there are greater changes in mode use among those with a lower level of education than there are for those with higher levels of education. This may reflect the impacts of the Great Recession, as those with lower levels of education (and lower income) may have been more impacted by the Recession. However, overall, there is a decrease in the use of active modes of transportation across all levels of education.

Table 5. Weighted[1] Trip Mode Share by Education Level

Trip Mode 2017	Less than a high school graduate	High school graduate or GED	Some college or associate degree		Bachelor's degree	Graduate or professional degree
All local bus types	4.3%	2.9%	1.9%	--	1.3%	1.1%
Bicycle	1.8%	0.8%	0.8%	--	1.3%	1.8%
Metro, rapid, trolley	0.3%	0.4%	0.4%	--	1.2%	1.4%
Private vehicle	74.7%	83.0%	84.8%	--	79.6%	78.0%
Taxi or hired car	0.3%	0.4%	0.5%	--	1.3%	0.8%
Walk	15.7%	11.1%	10.0%	--	13.3%	14.8%
Trip Mode 2012	**Not a high school graduate**	**High school graduate or GED**	**Some college credit but no degree**	**Associate or technical school degree**	**Bachelor's or undergraduate degree**	**Graduate or professional degree**
All local bus types	4.0%	4.0%	3.0%	2.0%	2.0%	2.0%
Bicycle	2.0%	1.0%	1.0%	1.0%	1.0%	2.0%
Metro, rapid, trolley	1.0%	1.0%	1.0%	1.0%	1.0%	1.0%
Private vehicle	69.0%	76.0%	80.0%	83.0%	81.0%	79.0%
Taxi or hired car	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Walk	22.0%	17.0%	13.0%	11.0%	13.0%	14.0%

[1] Weights present in the publicly available data were applied to the full sample, though not all modes are presented here; therefore, percentages do not add up to 100%.

[2] The less than high school category includes young children explicitly in 2012, and implicitly in 2017.

The last individual characteristic we explore is age. Age was not available as a continuous variable in the 2012 data, so we grouped the 2017 age information into the categories contained in the 2012 data as a continuous variable. These are presented in Figure 1 and Figure 2. The changes in mode share are fairly consistent across the age categories. All ages have higher use of private vehicle in 2017 than in 2012; represented by the yellow segments in each chart.

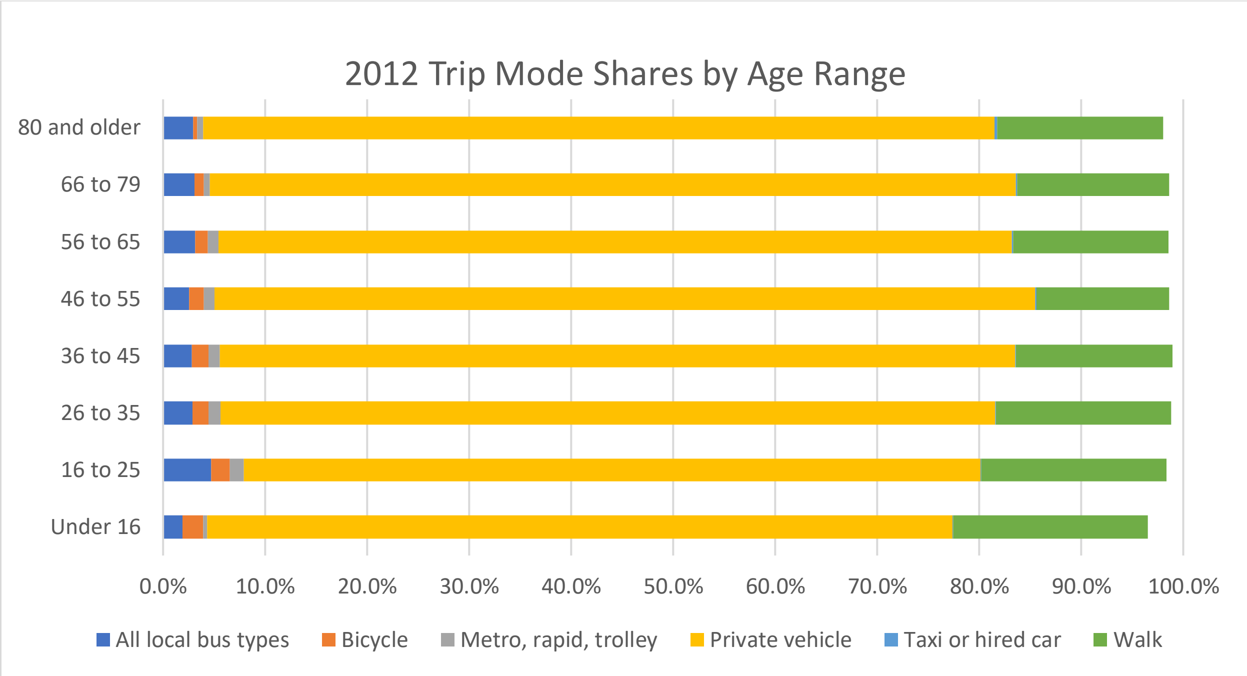

Figure 1. Weighted[1] 2012 Trip Mode Shares by Age Range

[1] Weights present in the publicly available data were applied to the full sample, though not all modes are presented here; therefore, percentages do not add up to 100%.

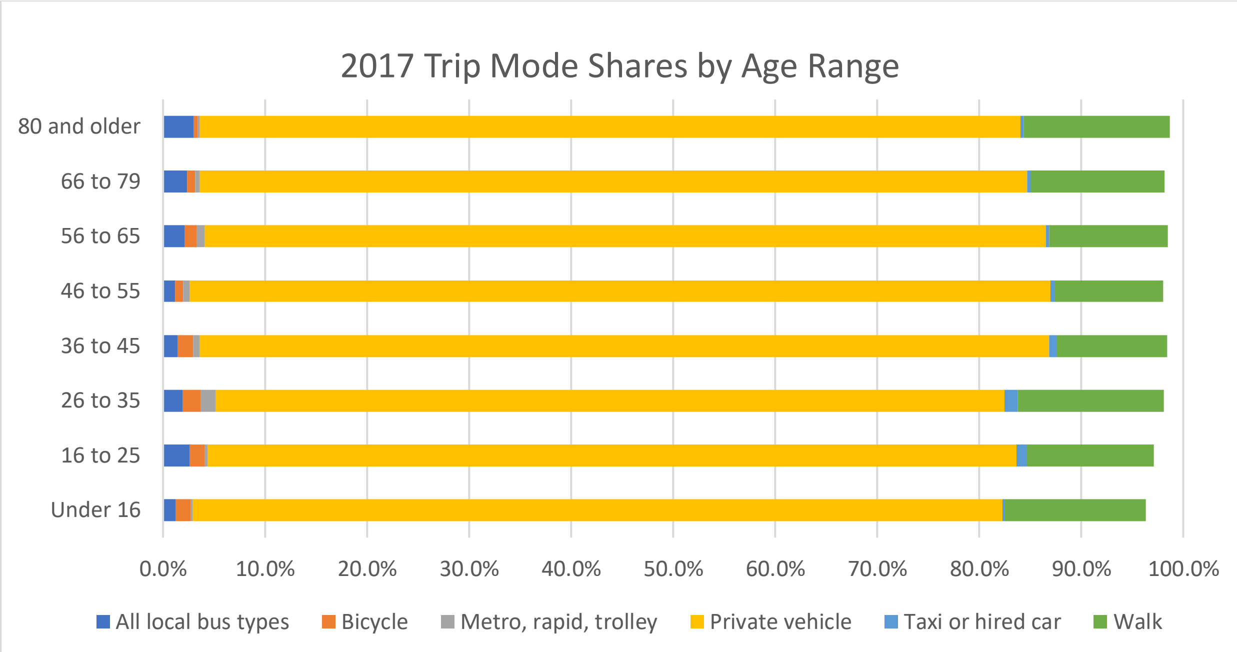

Figure 2. Weighted[1] 2017 Trip Mode Shares by Age Range

[1] Weights present in the publicly available data were applied to the full sample, though not all modes are presented here; therefore, percentages do not add up to 100%.

Now we turn to household level characteristics including household income and number of vehicles. Figure 3 and Figure 4 present trip mode shares by income category for 2012 and 2017. The income categories in the surveys are not identical, however for the descriptive statistics we keep them as they are in the survey data. In the models below we combine categories in order to include them in the model and have them the same for both years. Notable trends between 2012 and 2017 are the (known) higher trip mode shares for non-auto modes across all income categories for 2012. And, in 2017 the share of trips made by taxis or hired vehicles is larger than in 2012, though both are quite small overall.

The changes in non-auto mode shares are more pronounced within the lower income categories. For example, the share of trips made by walking (green in the chart) is 10-15 percentage points lower in 2017 than in 2012 for those whose reported income is in any category with an upper bound of less than $35,000. The change is much lower, 0-5 percentage points, for each of the higher income categories. This change may be due to increased levels of vehicle ownership among lower income households over the study period, though a number of factors likely contribute to changes in vehicle ownership.

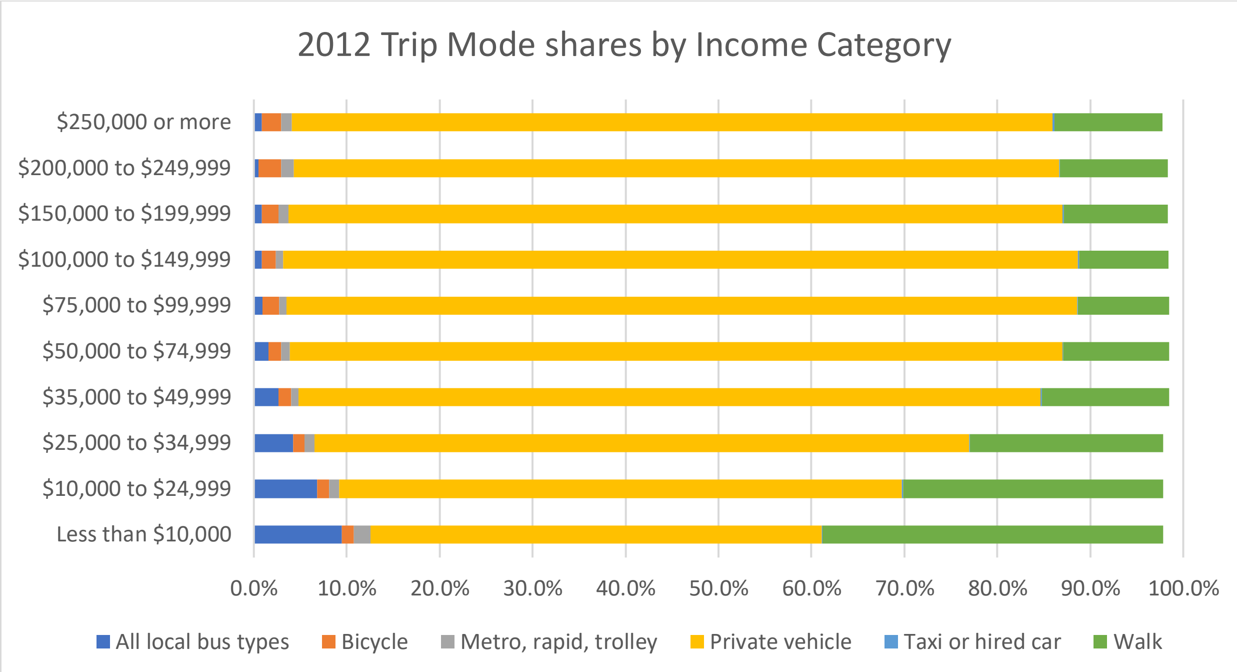

Figure 3. Weighted[1] 2012 Trip Mode Shares According to Income Category

[1] Weights present in the publicly available data were applied to the full sample, though not all modes are presented here; therefore, percentages do not add up to 100%.

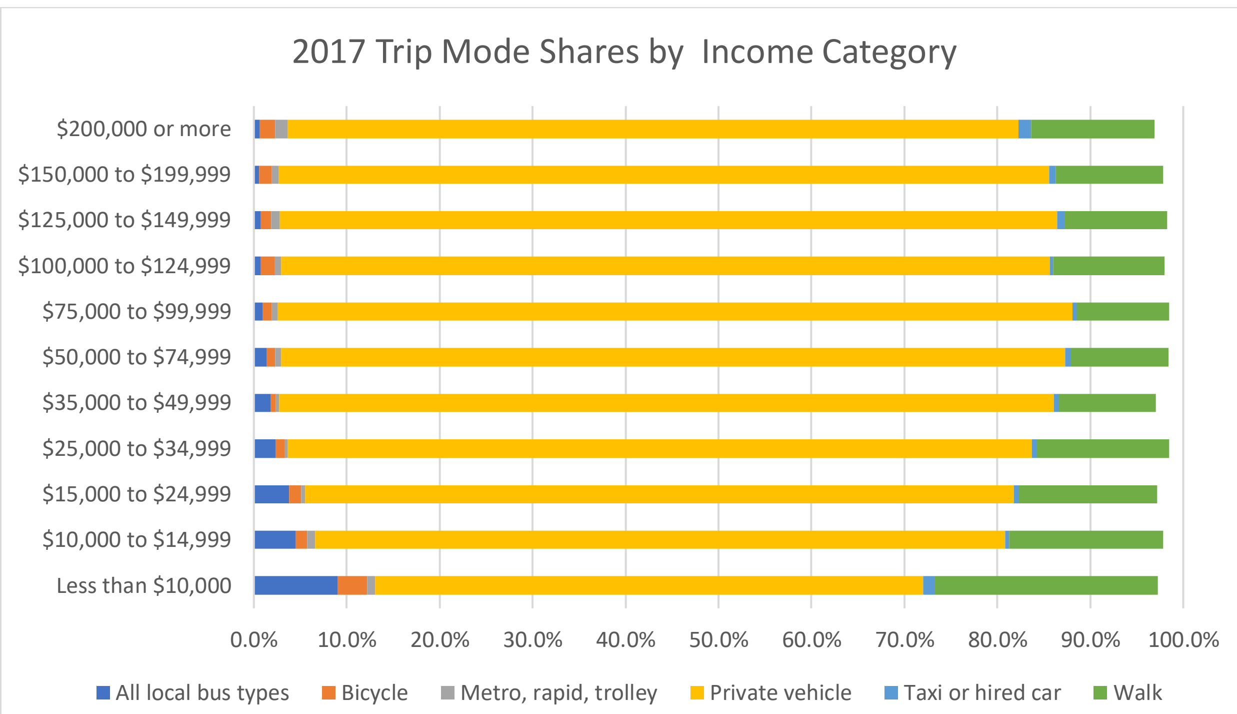

Figure 4. Weighted[1] 2017 Trip Mode Shares According to Income Category

[1] Weights present in the publicly available data were applied to the full sample, though not all modes are presented here; therefore, percentages do not add up to 100%.

The mode shares of different income groups changed more substantially for those with lower incomes, so it is useful to examine whether there are other changes along the lines of income that intersect with these shifts. To that end, we present the shares of Hispanic individuals in each income category.

Two notable patterns emerge: first that the proportion of Hispanic individuals at each point is higher in 2017 than it was in 2012, except for the lowest few income categories; namely incomes lower than $25,000 annually. This suggests that Hispanic individuals are earning somewhat more in 2017 than they were in 2012 and may also be an artifact of the increased proportion of the population that is Hispanic overall. Again, there seems to be a cut point around the annual income of $35,000. Below this income there are higher proportions of Hispanic individuals in 2012, but after this cut point there are higher proportions of Hispanic individuals in 2017.

Table 6. Weighted[1] Household Income Shares among Hispanic and non-Hispanic

	2012		2017	
Household Income	**Share Not Hispanic**	**Share Hispanic**	**Share Not Hispanic**	**Share Hispanic**
Less than $10,000	30%	70%	54%	46%
$10,000 to $14,999	---	---	47%	53%
$10,000 to $24,999	36%	64%	---	---
$15,000 to $24,999	---	---	49%	51%
$25,000 to $34,999	48%	52%	47%	53%
$35,000 to $49,999	59%	41%	53%	47%
$50,000 to $74,999	70%	30%	60%	40%
$75,000 to $99,999	77%	23%	63%	37%
$100,000 to $124,999	---	---	73%	27%
$100,000 to $149,999	81%	19%		
$125,000 to $149,999	---	---	69%	31%
$150,000 to $199,999	83%	17%	79%	21%
$200,000 to $249,999	87%	13%	---	---
$200,000 or more	---	---	85%	15%
$250,000 or more	91%	9%	---	---

[1] Weights present in the publicly available data were applied to the full sample,

We also consider driver's license according to income category. The results (in Table 7) are not as expected, but when considering the different question wording between 2012 and 2017 they make sense. That is, in 2017 the question asked if you drive, whereas in 2012 survey takers were asked if they have a license. The numbers are very similar for lower income groups across the two years (and two versions of the question). The proportion of individuals with a license/that drive grows along with income in both years. But, in 2017 the numbers drop off at just below 85%, likely because about 11-14% of those that have a license – with medium to high incomes – do not actually drive. This is not to say the reality was different in 2012, but that asking the question in the two different ways yields these different results; because having a license does not necessarily mean that you drive. What is most relevant to this study is the lower income levels, and here the percentages are quite similar overall, so it is not likely that there is a relationship between income and being/able-to-be a driver that is different in 2017 than in 2012. Income relates to driving in about the same way for all income groups below $35,000. It is possible though that the relationship between vehicle access and income did change over the study period.

Table 7. Weighted[1] Proportion of Drivers According to Income Category for 2012 and 2017

	2012		2017	
Income	**Share with License**	**Share no License**	**Share with License**	**Share no License**
Less than $10,000	55%	44%	55%	45%
$10,000 to $14,999	---	---	60%	40%
$10,000 to $24,999	67%	32%	---	---
$15,000 to $24,999	---	---	72%	28%
$25,000 to $34,999	78%	21%	76%	24%
$35,000 to $49,999	86%	14%	77%	23%
$50,000 to $74,999	92%	8%	80%	20%
$75,000 to $99,999	94%	6%	83%	17%
$100,000 to $124,999	---	---	84%	16%
$100,000 to $149,999	94%	5%	---	---
$125,000 to $149,999	---	---	81%	19%
$150,000 to $199,999	96%	4%	84%	16%
$200,000 to $249,999	96%	4%	---	---
$200,000 or more	---	---	82%	18%
$250,000 or more	97%	3%	---	---

[1] Weights present in the publicly available data were applied to the full sample,

Comparing household vehicles for drivers and non-drivers, in 2017 drivers are in households with an average of 2.4 vehicles compared to non-drivers who are in households that have 1.8 vehicles on average. These numbers are slightly lower in 2012; 1.7 household vehicles for those with a license and 2.2 for those without.

Considering Hispanic groups, we find that there are lower levels of driving among Hispanic than non-Hispanic individuals at both points in time. For Hispanic, as for the lower income groups above, we do not see a large shift in the number of drivers – that is in 2012 73% of the Hispanic individuals reported having a driver's license, while in 2017 72% reported being a driver. This differs from non-Hispanic travelers – where 92% report having a license in 2012 and 82% report that they are drivers. This is in line with the income results and the average for the sample overall: 90% in 2012 and 86% in 2017. The drop is likely due to the difference in question wording.

We also consider household vehicles as a factor that may impact mode shares. We calculate the average number of household vehicles for each trip mode and present the results in Table 8. The relationship between household vehicle counts and mode shares did not change substantially from 2012 to 2017. Overall, the mean number of household vehicles is fairly similar by mode across the two years; with slightly higher numbers of vehicles on average in 2012 than in 2017. Trips made by private vehicle tend to have a higher number of household vehicles. Bus trips tend to be made by individuals with fewer household vehicles. Walk, bike and metro trips were in the middle in terms of the number of household vehicles. The primary difference between 2012 and 2017 is for bus—there is a higher number of household vehicles in 2012 than in 2017 perhaps reflecting a desire to spend less on gas in 2012. That is, there is likely a shift from bus towards driving for households with higher numbers of vehicles in 2017 as opposed to 2012 when households even with higher numbers of vehicles may have driven less to save money. These results also do not show whether there are more households with higher numbers of household vehicles during this time, only that trips made by a particular mode tend to correspond with similar household vehicle counts in 2012 and 2017. And the effect of the number of household vehicles likely did not change over the study period, though the number of vehicles per household may have. So, we examine the changes in household vehicle counts by income, and Hispanic identity.

Table 8. Weighted[1] Mean Count of Household Vehicles by Trip Mode

Trip Mode	Mean household vehicle count 2017	Mean household vehicle count 2012
All local bus types	0.98	1.45
Bicycle	1.66	1.93
Metro, rapid, trolley	1.54	1.65
Private vehicle	2.38	2.21
Taxi or hired car	1.42	1.92
Walk	1.72	1.68

[1] Weights present in the publicly available data were applied to the full sample, though not all modes are presented here.

In Table 9 we present household vehicle counts with respect to income. The 2017 numbers are slightly higher than those of 2012 throughout all income levels (save less than $10,000 and $75,000 to $99,999 which both decrease slightly). The greatest changes occur for those with low (but not the lowest) incomes. Those in the very lowest income category (less than $10,000) may not be able to afford increased numbers of household vehicles at all. But for those with low incomes, there is likely a desire to purchase a vehicle when it is possible, and if vehicles became more available to these income groups in 2017 than in 2012 it is reasonable to expect households to purchase a (or an additional) vehicle.

Though this relationship is not especially strong, these results do suggest that households at lower income points were able to purchase higher numbers of household vehicles in 2017 than in 2012, either due to changes in vehicle or fuel prices, or other expenses that allowed more funds to be devoted to transportation at the household level. It could also be that households at these income levels were more willing to spend more on transportation at the expense of other household needs, or due to the burdens associated with not having a car or having too few cars to meet household needs. Manville et al. (2023) point out the relationship between transit use and car availability; higher levels of transit use are found for those who cannot afford vehicles and live in lower density areas where transit is harder to rely on as a primary means of transportation. This is contrasted with those who live in dense urban areas where car use is expensive, time-consuming, or otherwise burdensome (i.e., limited parking). If vehicle ownership becomes more plausible for the first group, they may be more likely to increase vehicle ownership and also to reduce transit use as a result.

Table 9. Weighted[1] Average Household Vehicle Counts by Household Income

Income category (adjusted so categories are the same for 2012 and 2017)	**Mean household vehicle count 2017**	**Mean household vehicle count 2012**
Less than $10,000	1.33	1.34
$10,000 to $24,999	1.65	1.50
$25,000 to $34,999	1.90	1.78
$35,000 to $49,999	2.09	1.96
$50,000 to $74,999	2.27	2.21
$75,000 to $99,999	2.35	2.36
$100,000 to $149,999	2.57	2.44
$150,000 to $199,999	2.65	2.56
$200,000 or more	2.61	2.54

[1] Weights present in the publicly available data were applied to the full sample.

We also explore changes in household vehicle counts with respect to Hispanic identity. Hispanic individuals had 1.99 household vehicles in 2012 and this increased to 2.26 in 2017; whereas the change is smaller for those who are not Hispanic. Average household vehicles of non-Hispanic individuals have a higher starting point of 2.18 in 2012 and increased only to 2.22 by 2017. There were greater increases in household vehicle counts for Hispanic individuals than others.

Lastly, trip rates may be declining over time, and there may be asymmetries in these declines across transportation modes, so an examination of trip rate patterns could provide additional insights into where these changes are happening. If there are greater declines among active modes, that might be part of the reason for the shift in mode shares. As use of a single mode decreases, other modes make up a larger portion of the trips overall even if travel with those modes does not increase absolutely. And this is, to some extent what we see in Table 10. The average number of trips made by someone who made a trip using the bus dropped from about 9.7 trips to 3.7 trips, and from about 9.8 to 4.0 for metro. These numbers are 5.2 to 4.6 for bike, 5.5 to 5.0 for private vehicle, 5.1 to 4.9 for taxi, and 7.1 to 5.1 for walk. For all modes there is a decline in the number of trips, with the greatest decline in both transit modes explored here. This matches known trends in transit ridership over this time period and suggests that the shift in mode shares over the study period is the result of declines in the amount of travel by those who use transit and walk (and possibly bike) and to a lesser extent, increases in the amount of travel among those who drive.

Table 10. Weighted[1] Average Trips on Travel Day by Mode for 2017 and 2012

Trip Mode	Mean trip count 2017	Mean trip count 2012
All local bus types	3.7	9.7
Bicycle	4.6	5.2
Metro, rapid, trolley	4.0	9.8
Private vehicle	5.0	5.5
Taxi or hired car	4.9	5.1
Walk	5.1	7.1

[1] Weights present in the publicly available data were applied to the full sample, though not all modes are presented here.

Finally, we consider trip characteristics including trip purpose and travel distance as these impact the mode used for an individual trip and are expected to be relevant to trip mode shares. Trip purpose is not consistent across the two surveys. Travel distances are similar overall, however the distances associated with the use of metro, rapid transit and trolley as well as local bus are substantially longer in 2017 than in 2012. Shorter trips were made with taxi and hired cars in 2017 than in 2012. This likely reflects TNC use for a greater share of shorter trips in 2017 than taxis were used for those shorter trips in 2012, and possibly a shift of shorter trips away from transit modes and towards TNCs.

Table 11. Weighted[1] Mean Trip Distance (in miles) by Trip Mode

Trip Mode	Weighted Mean Trip Distance 2012	Weighted Mean Trip Distance 2017
All local bus types	4.358	7.584
Bicycle	1.918	1.878
Private vehicle	7.22	8.803
Metro, rapid, trolley	9.644	14.732
Walk	0.497	0.551
Taxi or hired car	9.059	6.371

[1] Weights present in the publicly available data were applied to the full sample, though not all modes are presented here.

Multinomial Logistic Regression Models

This section presents multinomial logistic regression models for trip mode. We estimated separate models for 2012 and 2017, using the same set of explanatory variables. The results of the model estimations are presented in Table 12, below. Our main objective is to explore differences in the factors affecting the use of each mode between 2012 and 2017. This also means we consider which factors are potentially more important or have a stronger effect in each model. We subset the sample and included trips made with private vehicle, transit, walk, bike, and taxi. The transit mode includes local bus, Amtrak including bus, metro, rapid transit and trolley, and city-to-city bus. The base alternative in each model is private vehicle, so the coefficients in each model estimate the effect each explanatory variable has on the likelihood of choosing the alternative mode. The model estimations are not weighted because the weights are designed to produce population level statewide estimates of the outcomes (VMT, trip counts, etc.) and not for this kind of model.

Income categories were combined into three levels: low income includes all income levels less than $35,000. Medium income includes those within the range from $35,000 to $99,999, and high includes all income levels $100,000 or greater. Income was not included in the final model presented here. Income and education are highly correlated and education level improved model estimations more than income (based on rho-squared model diagnostic statistic). Variables are defined in the same way in each model so we may compare the magnitude of coefficients between models, with the exception of whether someone has a driver's license (2012) vs. being a driver (2017), as discussed above. This was ultimately not included in the models, as it is not possible to differentiate between the differences in the variable and the differences in effects between 2012 and 2017.

In general, the results of the multinomial models are as expected. Most of the coefficients are statistically significant, and generally with expected signs. Starting with the model for bicycle, in both models trips are more likely to be made by males than females, a known pattern for bicycle use. The effect of being male, all else equal may be slightly stronger in 2017 than in 2012, despite the descriptive statistics indicating that the share of bike trips among males is a little smaller in 2017 than it was in 2012. Age is not included in the 2012 model but has a small negative effect on bike as a trip mode in 2017. Education categories are included in the model, and those with a graduate degree are more likely to bike than others in 2017 and an insignificant effect in 2012. Other estimates make sense; Hispanic identity has a slightly stronger negative effect in 2017 than in 2012, as household vehicle count. The impact of trip distance is the same in both models.

In the models for the use of Taxi and hired vehicle, males are again more likely to use this mode than females, though the effect is not significant in the 2012 model. Age has a small negative impact in 2017. All of the education level variables are positive for this mode – those with the lowest levels of education not using these modes (similar to findings in other studies). These impacts are slightly stronger in 2017 than in 2012, except for those with a graduate degree, where the impact is similar in 2012 and 2017. All other variables are negative; higher household vehicle counts decrease the likelihood of taxi use in both years, though possibly with a stronger effect in 2012. Finally, Hispanic identity and trip distance do not have an impact on this mode in either model.

Turning to the models for transit, age has a small negative effect, and education is more mixed than in other models, with all education levels imparting a negative effect in 2017, but only "some college of associate degree" has a negative effect in 2012. In other words, the lowest education level contributes to driving in 2017, but not in 2012; individuals of various educational backgrounds were more likely to use transit in 2012. This is somewhat in line with the descriptive statistics in that the difference in the shares of transit trips in the lowest education level and higher levels is greater in 2017 than it is in 2012. Hispanic has a positive effect on transit use in 2012 and likely no effect in 2017 – this is not surprising as the trip mode shares of Hispanic individuals are more similar to the rest of the population in 2017 than in 2012. Higher household vehicle counts has a negative impact on transit both years, with a somewhat stronger effect in 2017.

Finally in the models for walk, age has a small effect, education levels have negative impacts in both models, except for the graduate degree, which has a small positive effect in 2012 and no effect in 2017. Hispanic identity contributes positively to walking in 2012 but negatively in 2017. This is in line with the descriptive statistics. Males are more likely that women to walk in both years, with a slightly stronger effect in 2017. Household vehicle counts have a negative impact on walking with a slightly lower effect in 2017.

Table 12. Multinomial Logistic Regression Models of Trip Mode in 2017 and 2012[1]

	2012 Trip Mode			2017 Trip Mode		
Variables in Model	**Coef. (exp^{β})**	**Std. Err.**	**p. value**	**Coef. (exp^{β})**	**Std. Err.**	**p. value**
Bicycle						
(Intercept)	-2.48	0.05	0.000	-1.49	0.10	0.000
Age				-0.02	0.00	0.000
High school graduate or GED	-0.55	0.05	0.000	-0.50	0.11	0.000
Some college or associates degree	-0.87	0.05	0.000	-0.50	0.10	0.000
Bachelor's degree	-0.28	0.04	0.000	-0.04	0.09	0.631
Graduate or professional degree	0.04	0.04	0.260	0.28	0.09	0.002
Hispanic	-0.57	0.04	0.000	-0.60	0.08	0.000
Male	0.93	0.03	0.000	1.07	0.05	0.000
Household Vehicles	-0.41	0.02	0.000	-0.55	0.02	0.000
Trip Distance (miles)	-0.22	0.01	0.000	-0.22	0.01	0.000
Taxi						
(Intercept)	-6.85	0.23	0.000	-3.26	0.23	0.000
Age				-0.03	0.00	0.000
High school graduate or GED	0.42	0.24	0.076	0.54	0.25	0.029
Some college or associates degree	0.27	0.22	0.210	0.54	0.23	0.018
Bachelor's degree	0.82	0.20	0.000	1.38	0.22	0.000
Graduate or professional degree	1.20	0.20	0.000	1.18	0.22	0.000
Hispanic	0.10	0.15	0.507	-0.17	0.12	0.158
Male	0.10	0.11	0.349	0.19	0.08	0.014
Household Vehicles	-0.30	0.07	0.000	-0.74	0.05	0.000
Trip Distance (miles)	0.00	0.00	0.095	0.00	0.00	0.382

Variables in Model	2012 Trip Mode			2017 Trip Mode		
	Coef. (exp^{β})	Std. Err.	p. value	Coef. (exp^{β})	Std. Err.	p. value
Transit						
(Intercept)	-2.37	0.04	0.000	-0.76	0.09	0.000
Age				-0.02	0.00	0.000
High school graduate or GED	0.19	0.04	0.000	-0.23	0.09	0.009
Some college or associates degree	-0.14	0.04	0.000	-0.56	0.08	0.000
Bachelor's degree	0.19	0.04	0.000	-0.26	0.08	0.001
Graduate or professional degree	0.34	0.04	0.000	-0.25	0.08	0.002
Hispanic	0.64	0.03	0.000	0.04	0.06	0.460
Male	0.14	0.02	0.000	0.31	0.04	0.000
Household Vehicles	-0.93	0.02	0.000	-1.28	0.03	0.000
Trip Distance (miles)	0.00	0.00	0.000	0.01	0.00	0.000
Walk						
(Intercept)	1.29	0.03	0.000	2.22	0.05	0.000
Age	---	---	---	-0.01	0.00	0.000
High school graduate or GED	-0.34	0.02	0.000	-0.52	0.05	0.000
Some college or associates degree	-0.52	0.02	0.000	-0.51	0.05	0.000
Bachelor's degree	-0.17	0.02	0.000	-0.10	0.05	0.040
Graduate or professional degree	0.06	0.02	0.004	0.00	0.05	0.991
Hispanic	0.32	0.02	0.000	-0.20	0.03	0.000
Male	0.14	0.01	0.000	0.20	0.02	0.000
Household Vehicles	-0.40	0.01	0.000	-0.27	0.01	0.000
Trip Distance (miles)	-1.90	0.01	0.000	-2.31	0.02	0.000

1 Rho-squared model diagnostic was computed for each model, using a "constants-only" model as the base with which to compare the model outcome. The formula for this diagnostic statistic is: Rho-squared = (1 – (logLik(full model)/logLik(constants only model)). This value is 0.451 for the 2017 model, and 0.422 for the 2012 model. While these are fairly large, they may be in line with other models that use this large sample from the national and state level household travel surveys.

The model estimations presented here show effects that are largely in line with the descriptive statistics. Alternative model specifications were explored, including those with income, and whether the trip was made by someone with a license/a driver. The variables retained in these models had a better diagnostic statistic than alternative specifications and were retained for presentation here. Estimations were also evaluated using interaction terms, for Hispanic, and income categories interacted with household vehicle counts. Most of these effects were not significant, though alternative interaction terms could be explored in future research.

Discussion and Conclusions

This exploratory analysis investigates factors contributing to the decrease in biking, walking and transit use in California over the period from 2012 to 2017. We focus on variables that are present in the 2012 CHTS and the 2017 NHTS California add on sample. We evaluate descriptive statistics to identify variables that are related to the changes in mode shares. Model estimations further explore these relationships by evaluating the effects of multiple variables.

The primary limitation of the present study is the difficulty in incorporating information on the changes in the population over time. The outcomes presented here tend to show that while there are some changes within individual groups; for example, Hispanic individuals are more likely to make trips with private vehicle in 2017 than in 2012, the overall effect that this has on mode shares is likely a combination of this shift within the group along with an effect that results from this group making up a larger portion of the population. Similarly, if Californian's are earning more (or less) in 2017 than in 2012 we do not know if that shift has had an effect, only that the relationship between income and mode use has changed to some extent over the study period. While this is a limitation, there are some within group effects observed here, suggesting that the choices made by individuals in those groups have changed over time.

In addition, we did not exhaust every plausible variable for inclusion in the models. The presented models do a reasonably good job of explaining a lot of the variation and are not lacking in terms of explanatory power. That being said, there are additional factors in each dataset that could be explored for inclusion in models of trip mode share. Finally, the choice of using trip mode does have some limitations, though trip mode share does capture the trends for all trips made at the time of each survey.

Our descriptive statistics show that Hispanic individuals made more changes away from active modes than those with other ethnic identities. Education also plays a role in the observed mode share changes with individuals with lower education level making more changes. Similarly, individuals in lower income households more likely to shift from the use of active modes, and in particular away from walking and increase the use of private vehicles. Individuals in less advantaged groups were more likely to decrease their use of biking, walking and transit over the study period.

This may mean that conditions changed over the time period from 2012 to 2017 and more individuals from these disadvantaged groups were able to purchase and/or use household vehicles in 2017 than in 2012. These results suggest that, when possible, travel by private vehicle has benefits that are not necessarily afforded by using alternative modes. Those who use alternative modes may do so only when it is impossible or unaffordable to drive or use private vehicles, or when there are real conditions that make private vehicle use more difficult than using alternative modes.

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Data Summary

Products of Research

This study used two publicly available data sources: the 2017 National Household Travel Survey data, and the California Household Travel Survey data.

The National Household Travel Survey data can be downloaded from the Oak Ridge National Laboratory here: https://nhts.ornl.gov/. The following citation is recommended for users of the data: U.S. Department of Transportation, Federal Highway Administration, 2017 National Household Travel Survey. URL: http://nhts.ornl.gov.

The California Household Travel Survey data can be downloaded from the National Renewable Energy Lab here: https://www.nrel.gov/transportation/secure-transportation-data/download.html. You must register as a user in order to download the data. The following citation is recommended: Transportation Secure Data Center. (2017). National Renewable Energy Laboratory. Accessed Jan. 15, 2017: www.nrel.gov/tsdc

Data Format and Content

The data can be downloaded in a variety of formats from the sources noted above.

Data Access and Sharing, and Reuse and Redistribution

See above.