Updated Default Values for Transit Dependency and Average Length of Unlinked Transit Passenger Trips, for Calculations Using TAC Methods for California Climate Investments Programs

Technical Report

California Climate Investments Quantification Methods Assessment
California Air Resources Board
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Section A. Introduction

Under California's Cap-and-Trade program, the State's portion of the proceeds from Cap-and-Trade auctions is deposited in the Greenhouse Gas Reduction Fund (GGRF). The Legislature and Governor enact budget appropriations from the GGRF for State agencies to invest in projects that help achieve the State's climate goals. These investments are collectively called California Climate Investments.

Senate Bill (SB) 862 requires the California Air Resources Board (CARB) to develop guidance on reporting and quantification methods for all State agencies that receive appropriations from the GGRF. Guidance includes developing quantification methodologies for estimating greenhouse gas (GHG) emission reductions and other social, economic, and environmental benefits of projects, referred to as "co-benefits." CARB develops quantification methodologies to provide project-level GHG emission or co-benefit estimates that are supported by empirical literature. This work relies on a review of the available science, coordination with the administering agencies, and outside experts and academic partners to obtain technical assistance and expertise, as needed.

The quantification methodologies are developed to:

- Support calculating the estimated GHG emission reductions and applicable co-benefits for individual projects;
- Apply to the project types proposed for funding;
- Provide uniform methodologies that can be applied statewide and are accessible by all applicants;
- Use existing and proven tools or methodologies, where available;
- Include the expected period of time for when GHG emission reductions and co-benefits will be achieved; and
- Identify the appropriate data needed to calculate GHG emission reductions or co-benefits.

CARB may review and update GHG quantification methodologies and co-benefit assessment methodologies periodically based on: new or evolving project types; new legislation; available resources; new scientific developments or tools, or modifications in the analytical tools or approaches upon which the methodologies were based; or input from administering agencies or the public.

This report addresses aspects of CARB's current quantification methods for estimating GHG emission reductions from projects that expand transit facilities or service. A number of California Climate Investments programs fund transit projects, including the Low Carbon Transit Operations Program (LCTOP), the Transit and Intercity Rail Capital Program (TIRCP), and the Affordable Housing and Sustainable Communities (AHSC) Program. CARB has developed technical documents for each program, called "Quantification Methodologies," and associated spreadsheet calculation tools, called "Benefit Calculator Tools," for program applicants to use in estimating project-level

GHG emission reductions and co-benefit estimates for projects proposed for funding.[1] State administering agencies then employ the results when selecting projects for funding from these programs and for reporting purposes. To measure GHG emission reductions from transportation projects, including transit projects, CARB relies on "CMAQ" computation methods, published by CARB in 2005 with the California Department of Transportation (Caltrans) for evaluating motor vehicle fee registration projects and congestion mitigation and air quality improvement (CMAQ) projects, specifically transit and connectivity (TAC) features.[2]

This report addresses how and whether CARB might update default values for two adjustment factors employed in the TAC methods that apply to transit facility and/or service expansion projects. The first factor is used to account for transit dependency in estimating ridership gains from a new transit project, indicating the projected share of riders of a new project who will not be transit dependent, and therefore could be expected to have driven in the absence of the project. The second factor is a required input for the estimated length of an average unlinked transit passenger trip associated with a proposed project.

The report also summarizes recent research on transit dependency and factors that influence transit ridership, to inform an understanding of how these factors may influence California Climate Investments programs.

[1] The quantification methodology documents and associated computation tools are available at www.arb.ca.gov/cci-resources.

[2] California Air Resources Board. *Methods to Find the Cost-Effectiveness of Funding Air Quality Projects for Evaluating Motor Vehicle Registration Fee Projects and Congestion Mitigation and Air Quality Improvement Projects*. May 2005. www.arb.ca.gov/planning/tsaq/eval/eval.htm.

Section B. Current Quantification Method

To estimate GHG emission reductions and selected co-benefits from transit projects proposed for funding from California Climate Investments programs, CARB employs the TAC methods noted above. GHG emission reductions are calculated based on an estimate of the annual reduction in vehicle miles traveled (VMT) from "displaced" auto usage attributable to the proposed project. For new or expanded service, the full estimate is calculated as the difference between the emission reductions from displaced autos and the emission associated with the operation of the new/expanded service.

This report evaluates how CARB could update two default adjustment factors used in the TAC methods, and in CARB's quantification methodologies for estimating emission reductions from transit projects. The first, an "A" factor, is used to account for transit dependency in estimating ridership gains. The factor is used to indicate the share of riders of transit projects who are not transit dependent, and therefore could be expected to have driven in the absence of the project. The second, an "L" factor, is a required input for the estimated length of an average unlinked transit passenger trip associated with the proposed project. This report does not address other aspects of the TAC methods for transit projects beyond these two factors.

The adjustment factors addressed in this report appear as "A" and "L" in the following equation (Figure 1), reproduced from page 37 in CARB's Fiscal Year 2018-19 Quantification Methodology for the Transit and Intercity Rail Capital Program (TIRCP) (essentially the same equation is presented in the Quantification Methodology documentation for the LCTOP and AHSC programs).[3] Applicants seeking funds for transit projects from these programs are expected to provide input information for the "R," "A," and "L" factors shown in the equation. For the "R" factor, program applicants are expected to use information supplied by the transit agency that will build and/or operate the project, as per the case study examples offered in CARB's documentation. For the "A" and "L" factors, applicants may use default data provided

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[3] The TAC methods technical documentation provides a slightly different estimation equation, namely: Annual Auto VMT Reduced = [(D)*(R)*(A)]*[(L) - (AA)*(LL)], where D equals days of operation per year, R equals trips per day, A equals the adjustment for transit dependency, representing the portion of transit riders who reduce a vehicle trip, L equals length of average auto trips reduced, AA equals an adjustment on auto trips for auto access to and from transit service, representing the portion of riders who drive to the transit service, and LL equals trip length for auto access to and from transit. This is essentially the same equation as in the California Climate Investments program quantification methodologies except for the addition of the adjustment for auto travel to and from transit access. The documentation provides default values, with no cited sources for the following factors: auto trip length (L) = 9 miles, or for work trip bus services, 16 miles, or for school bus, 3 miles; adjustment for transit dependency (A) = 0.5, or 0.83 for commuter bus service; auto access (AA) = 0.1, or 0.8 for long-distance commuter service; trip length (LL) for auto access to and from transit = 2 miles, or 5 miles for long-distance bus service. See pages 16-18 in the CMAQ technical documentation.

in the documentation, if project-specific data or results from a cited statistically valid survey are not available to the applicant.

This report suggests methods to update the default values that CARB provides for the “A” and “L” factors. As indicated, the “A” adjustment factor is used to represent the share of transit riders *not* dependent on transit (and therefore who would have driven instead). Based on the TAC methods, CARB’s quantification methodology documentation supplies two default values for this factor, one for “local service” (0.50) and the other for “long-distance service, shuttles, and vanpools” (0.83). The TAC methods technical documentation does not provide a cited evidence basis for the default values provided for this factor. This report provides an updated set of “A” factor default values, with a cited evidence basis.

Equation 1: Annual Auto VMT Reduced in Miles per Year

$$AutoVMT = [(R) * (A) * (L)]$$

Where,			<u>Units</u>
R	=	Annual **increase** in unlinked passenger trips[1] directly associated with the proposed project	Riders
A	=	Adjustment factor to account for transit dependency Use: documented project-specific data or system average developed from recent, statistically valid survey or default. Default: 0.5 for local service or 0.83 for long-distance service, shuttle and vanpools.	Unitless
L	=	Estimated length of average unlinked passenger trip directly associated with the proposed project, calculated as passenger-miles[2] divided by unlinked trips. Applicants may use data reported to National Transit Database[i] for similar service or refer to Appendix C.	Mile-rider

[1] Unlinked passenger trips are defined as the number of passengers who board public transportation vehicles.
[2] The cumulative sum of the distances ridden by each passenger.

Figure 1. Estimation equation for annual auto VMT reduced from transit projects, from TAC methods. The annual auto VMT reduced is estimated as the product of the annual increase in unlinked passenger trips directly associated with the project; the adjustment factor for transit dependency; and the estimated length of average unlinked passenger trips directly associated with the proposed project.

For the “L” factor, applicants are directed to use data from the National Transit Database (NTD) for similar type of service, or to refer to Appendix C in the TIRCP Quantification Methodology document, which contains look-up tables for lengths of average unlinked passenger trips by mode, both statewide and for individual transit agencies, using data from the NTD. CARB's Appendix Table C-1 shows statewide values by mode. CARB's Appendix Table C-2 shows values by mode for individual transit agencies in California.

An investigation of NTD data indicates that 2016 is the most recent year for which data are available, as of the time this report was authored. This report provides updated values for CARB's Appendix Table C-1 and C-2, derived from the 2016 NTD.

Section C. Definition and characteristics of the transit dependent

The main objective of the literature review undertaken for this report was to determine a viable method for estimating transit dependency, in order to be able to update the "A" factor for transit non/dependency utilized in the TAC methods. The research was needed to update the default values for the "A" factor provided in the TAC methods with the latest available research. By contrast, the derivation and use for the "L" factor values, also addressed in this report, are more transparent and straightforward, and did not require any methodology review in order to update.

In evaluating transit dependency, a useful first step is to consider how characteristics of transit riders differ from the overall population. Compared to the general population in the United States (US), transit riders tend to be younger overall and more likely to be people of color. People of color make up a majority of riders (60%), with African-American riders comprising the largest single group (24%) (Clark, 2017).[4] Transit users are also considerably more likely to have lower incomes; although 13% of US households had household incomes of less than $15,000 in 2014, 21% of transit-using households had incomes below this level.[5] However, when it comes to average household size, unemployment rates, and number of worker in the household, transit users resemble the overall population nationally.

Manville and co-authors (2018) found similar distinctions when comparing transit users to non-users in the 6-county Los Angeles metropolitan area, using survey data from the 2013 California Household Travel Survey (CHTS).[6] The authors found distinctions based on race/ethnicity, immigrant status, and income. They found that African Americans and Latinos in the Los Angeles region were three times more likely to ride transit than white non-Hispanics and Asians. Immigrants who had been in the country less than ten years rode substantially more than both the native-born and longtime immigrants who had been in the country longer. People in households earning under $25,000 per year were more than twice as likely to use transit as people in households earning $25,000 to $50,000, and in turn people from these households were more than twice as likely to use transit as people from households earning over $50,000 annually.

However, the factor that Manville and co-authors found to form the most noticeable contrast between transit users and non-users was vehicle availability. People in

[4] These findings come from a summary of results compiled from 211 separate passenger survey reports conducted between 2008 and 2015 representing the services of 163 transit systems throughout the US.
[5] Population data were based on American Community Survey 5-year estimates presented in 2014 inflation adjusted dollars, while transit rider incomes are based on 211 separate passenger survey reports conducted between 2008 and 2015, inflation-adjusted to 2015 dollar levels (Clark, 2017).
[6] The CHTS is conducted by Caltrans every ten years to obtain detailed information about the socioeconomic characteristics and travel behavior of households statewide. The last CHTS was conducted from January 2012 to January 2013.

households without a vehicle were almost five times as likely to make transit trips as those in households with one vehicle, and people in households with one vehicle twice as likely as those with two vehicles (Manville et al., 2018). This finding supports the validity of using access to a vehicle as a primary indicator of transit dependency.

Access to a vehicle has been a central consideration for scholars seeking to identify and distinguish "transit-dependent" riders, those who do not have an alternative to using transit for a given trip, from "choice" transit riders, those with a car available, but who choose to use public transit because of its comparative advantage for a given trip. As in the case of this report, one reason that scholars and planners have sought to distinguish these two groups is to be able to accurately assess the impact of transit improvements on patterns of driving. Another focus of concern has been equity-related, for example in considering how transit accessibility affects different socioeconomic groups, with associated benefits and burdens (Grengs et al., 2013; Karner et al., 2016). Still other scholars have focused not on the transit-dependent segment but rather upon "choice" riders, seeking to understand travel preferences of this group in order to try to identify strategies to attract more such riders (Krizek and El-Geneidy 2007).

A commonly accepted definition for transit dependent riders is whether they live in a household with no private vehicle available (Grengs et al., 2013, for FTA; Lachapelle et al., 2016; Clark, 2017, for APTA). This definition is often used although scholars recognize that a household's experience of accessibility is more complicated than such a simple assumption suggests; for example, people in carless households are not necessarily dependent on transit, as they may share rides with car owners or choose housing locations within walking distance of work, and by contrast, people in households with a car are not necessarily able to use it, for instance, if they rely on transit because the number of workers in the household exceeds the number of cars (Lovejoy and Handy, 2008; Grengs et al., 2013).

Nationally, surveys conducted between 2008 and 2015 indicate that 39% of transit riders had a car available to make their current trip, while 54% had a car available at least sometimes on an ongoing basis (Clark, 2017). In the Los Angeles area, annual surveys conducted between 2010 and 2016 by the region's largest transit operator, LA Metro, indicate that about 30% of transit users had a vehicle available to make their trip (Manville et al., 2018). The proportion was lower among bus riders than rail riders, but even among rail riders only about 40% reported having a vehicle available for their current trip.

Section D. Updated Values for the "A" and "L" Factors

Updated values for the "A" factor—the adjustment for transit non-dependency—were obtained for this report using the 2013 CHTS. The CHTS is a survey conducted every ten years by Caltrans. It is used for forecasting in regional and state travel models, among other purposes. The most recent CHTS was conducted from January 2012 to January 2013. Data are provided by household for all trips during a given day. The survey was conducted to be representative of all households residing in the 58 counties in California; a total of 42,431 households completed the survey. The CHTS provides the most comprehensive and most recent travel survey data designed to be statistically valid statewide, and which contains information on car ownership as well as travel patterns for all trips by mode.

Table 1 provides values computed from the CHTS that CARB can utilize to update the "A" factor for transit non-dependency presented earlier in the report (in Figure 1), used to determine auto VMT reductions from California Climate Investments-funded transit projects.[7] The current default values, seen in Figure 1, are 0.50 for "local service" and 0.83 for "long-distance service, shuttles, and vanpools." However, instead of providing only two default values based on length of trip, the CHTS-based analysis, shown in Table 1 provides values for transit non-dependency for specific travel modes, as available in the CHTS (the non-dependency value column is indicated by a bold outline in the table).

Using the data analysis presented in Table 1 as a basis for updating the required transit non-dependency "A" factor default values could provide greater accuracy granularity. First, California Climate Investments program applicants are more likely to know the modal type of transit project for which they are seeking funds than the length of trips that project users are likely to make. Second, the mode choices presented in Table 1 provide more variation in average trip lengths and non-dependency shares.

[7] The values in Table 1 are produced from the CHTS using the person-trip weight available in the "place" table.

Table 1. Transit non-dependency factors by mode, estimated from 2013 CHTS database

Mode of travel	Average trip distance in miles	N (# of survey observations) HH has car	N HH has no car	Weighted percentage of unlinked trips HH has car	HH has no car	Total	95% confidence interval for weighted proportion has-car	
Private shuttle (SuperShuttle, employer, hotel, etc.)	12	525	74	87.9	12.1	100	85.3	90.5
Greyhound bus	85	10	2	96.5	3.5	100	n/a	n/a
Other private transit	18	287	45	82.7	17.3	100	78.6	86.8
Local bus, rapid bus	4	3,438	2,924	56.1	43.9	100	54.9	57.3
Express bus/Commuter bus (AC Transbay, Golden Gate Transit, etc.)	16	256	81	70.5	29.5	100	65.6	75.4
Premium bus (Metro Orange/Silver Line)	9	64	41	54.2	45.8	100	44.5	63.9
Public transit shuttle (DASH, Emery Go-Round, etc)	3	125	50	58.5	41.5	100	51.1	65.8
Dial-a-Ride/ParaTransit (Access Services, etc.)	8	131	90	54.0	46.0	100	47.4	60.6
Amtrak bus	93	22	2	59.9	40.1	100	n/a	n/a
Other bus	7	69	28	66.1	33.9	100	56.5	75.7
BART, Metro Red/Purple Line	13	1,405	283	79.4	20.6	100	77.5	81.4
ACE, Amtrak, Caltrain, Coaster, Metrolink	40	461	55	86.7	13.3	100	83.7	89.6
Metro Blue/Green/Gold, Muni Metro, Sacramento Light Rail, San Diego Sprinter/ Trolley/Orange/ Blue/Green, VTA Light Rail	7	733	272	68.5	31.5	100	65.6	71.4
Street car/Cable car	4	50	42	47.9	52.2	100	37.4	58.3
Other rail	6	88	21	73.8	26.2	100	65.5	82.2
Ferry/Boat	15	96	0	100.0	0.0	100	100.0	100.0
Total	7	7,760	4,010	62.9	37.1	100	62.0	63.8

The analysis of CHTS data presented in Table 1 indicates that some transit mode categories for which average trips are relatively short have non-dependency shares similar to the current CARB default for "local service" (50%), including "local/rapid bus" (56.1%) and "streetcar/ cable car" (47.9%). Other modes shown in Table 1 for which average trips are longer have non-dependency shares similar to CARB's default for "long-distance service, shuttles, and vanpools" (83%), including "private shuttle" (87.9%), "BART/Metro red/purple line" (79.4%), and "ACE/Amtrak/Caltrain/etc" (86.7%). Other modal values in Table 1 fall in between the two current default values, including those for light rail lines (68.5%) and "express bus/commute bus" (70.5%).

For the sake of sample size, or for other reasons, CARB might consider restricting the number of modal options from Table 1 that program applicants are asked to select among, and/or CARB might choose to aggregate modal categories (in which case, appropriate non-dependency values would need to be calculated from the CHTS data for aggregated categories). Some mode categories shown in Table 1 contain too few survey responses (too small sample sizes) to be considered valid for providing accurate results; these modes are greyed out in the table (and confidence intervals are not calculated because the estimate is considered inappropriate for such small sample sizes). CARB might also consider aggregating categories shown in the table to produce a more limited set of options corresponding to the California Climate Investments project types eligible for funding.

To update CARB's default values for the "L" factor representing average length of trips, this report presents data findings derived from the 2016 NTD, produced by the Federal Transit Administration. Table 2 shows NTD-derived data values produced for this report that can be used to update the information on average trip lengths, currently provided in Appendix Table C-1 of CARB's TIRCP Quantification Methodology document.

Table A1 in the appendix of this report provides updates to Appendix Table C-2 of CARB's TIRCP Quantification Methodology document, which shows average length of trips by transit agency statewide. The data shown in this report are nearly identical to the data in CARB's table, as both are derived from the 2016 NTD (the latest year for which full information is available as of the time this report was authored).

Table 2. Length of average trip in California statewide by mode, from 2016 National Transit Database

Mode (code)	Average trip length (miles)*	Mode description
Commuter Bus (CB)	17.99	Local fixed-route bus transportation primarily connecting outlying areas with a central city. Characterized by a motorcoach (aka over-the-road bus), multiple trip tickets, multiple stops in outlying areas, limited stops in the central city, and at least five miles of closed-door service.
Cable Car (CC)	1.25	A transit mode that is an electric railway with individually controlled transit vehicles attached to a moving cable located below the street surface and powered by engines or motors at a central location, not onboard the vehicle.
Commuter Rail (CR)	28.98	An electric or diesel propelled railway for urban passenger train service consisting of local travel which operates between a central city and outlying areas. Service must be operated on a regular basis by or under contract with a transit operator for the purpose of transporting passengers within urbanized areas (UZAs), or between urbanized areas and outlying areas. Commuter rail is generally characterized by multi-trip tickets, specific station-to-station fares, railroad employment practices, relatively long distance between stops, and only 1-2 stations in the central business district.
Demand Response (DR)	8.30	A transit mode comprised of passenger cars, vans or small buses operating in response to calls from passengers or their agents to the transit operator, who then dispatches a vehicle to pick up the passengers and transport them to their destinations. A demand response (DR) operation is characterized by the following: a) The vehicles do not operate over a fixed route or on a fixed schedule except, perhaps, on a temporary basis to satisfy a special need, and b) Typically, the vehicle may be dispatched to pick up several passengers at different pick-up points before taking them to their respective destinations and may even be interrupted en route to these destinations to pick up other passengers. The following types of operations fall under the above definitions provided they are not on a scheduled fixed route basis: many origins - many destinations; many origins - one destination; one origin - many destinations; and one origin - one destination.
Demand Response-Taxi (DT)	10.94	A special form of the demand response mode operated through taxicab providers. The mode is always purchased transportation type of service.
Ferryboat (FB)	11.81	A transit mode comprised of vessels carrying passengers over a body of water. Intercity ferryboat (FB) service is excluded, except for that portion of such service that is operated by or under contract with a public transit agency for predominantly commuter services. Predominantly commuter service means that for any given trip segment (i.e., distance between any two piers), more than 50 percent of the average daily ridership travels on the ferryboat on the same day.
Heavy Rail (HR)	11.33	A transit mode that is an electric railway with the capacity for a heavy volume of traffic. It is characterized by: a) High speed and rapid acceleration passenger rail cars operating singly or in multi-car trains on fixed rails; b) Separate rights-of-way (ROW) from which all other vehicular and foot traffic are excluded; c) Sophisticated signaling, and d) High platform loading.
Light Rail (LR)	5.16	A transit mode that typically is an electric railway with a light volume traffic capacity compared to heavy rail (HR). It is characterized by: a) Passenger rail cars operating singly (or in short, usually two car, trains) on fixed rails in shared or exclusive right-of-way (ROW); b) Low or high platform loading; and c) Vehicle power drawn from an overhead electric line via a trolley or a pantograph.
Bus (MB)	3.94	A transit mode comprised of rubber-tired passenger vehicles operating on fixed routes and schedules over roadways. Vehicles are powered by diesel, gasoline, battery, and/or alternative fuel engines contained within the vehicle.

Table 2 (continued)

Monorail/ Automated Guideway (MG)	3.20	An electrically-powered mode of transit operating in an exclusive guideway or over relatively short distances. The service is characterized by either monorail systems with human-operated vehicles straddling a single guideway or by people-mover systems with automated operation.
Bus Rapid Transit (RB)	6.44	Fixed-route bus systems that operate at least 50 percent of the service on fixed guideway. These systems also have defined passenger stations, traffic signal priority or preemption, short headway bidirectional services for a substantial part of weekdays and weekend days; low-floor vehicles or level-platform boarding, and separate branding of the service. Agencies typically use off-board fare collection as well. This is often a lower-cost alternative to light rail.
Streetcar Rail (SR)	1.48	This mode is for rail transit systems operating entire routes predominantly on streets in mixed-traffic. This service typically operates with single-car trains powered by overhead catenaries and with frequent stops.
Trolleybus (TB)	1.50	A transit mode comprised of electric rubber-tired passenger vehicles, manually steered and operating singly on city streets. Vehicles are propelled by a motor drawing current through overhead wires via trolleys, from a central power source not onboard the vehicle.
Vanpool (VP)	44.56	A transit mode comprised of vans, small buses and other vehicles operating as a ride sharing arrangement, providing transportation to a group of individuals traveling directly between their homes and a regular destination within the same geographical area. The vehicles shall have a minimum seating capacity of seven persons, including the driver. For inclusion in the NTD, it is considered mass transit service if it meets the requirements for public mass transportation and is publicly sponsored. Public mass transportation for vanpool programs must: be open to the public; be actively engaged in advertising the vanpool service to the public and in matching interested members of the public to vans with available seats; whether operated by a public or private entity, be operated in compliance with the Americans with Disabilities Act of 1990 and implementing regulations at 49 CFR 37.31; and have a record-keeping system in place to meet all NTD reporting requirements.
Hybrid Rail (YR)	8.71	Rail system primarily operating routes on the national system of railroads, but not operating with the characteristics of commuter rail. This service typically operates light rail-type vehicles as diesel multiple-unit trains (DMU's). These trains do not meet Federal Railroad Administration standards, and so must operate with temporal separation from freight rail traffic.

*Calculated by dividing passenger miles traveled by unlinked passenger trips.

Section E. Research on Factors Influencing Transit Ridership

This report concludes with two sections discussing recent research on factors influencing transit ridership, including transit dependency. The research is indirectly relevant to the updating of the “A” and “L” factors in the TAC methodology, discussed above, providing a context for considering the relative influence of transit dependency versus other factors that influence ridership, including service improvements of the sort funded by California Climate Investments programs. Some research considering recent patterns in transit dependency in Southern California is also discussed, pointing to a change in the impact of this factor on ridership.

As noted earlier, researchers have sometimes sought to distinguish two transit user groups, choice riders and dependent riders, so as to evaluate their sociodemographic profiles, needs, preferences, and constraints (for example, time constraints), and how these factors affect ridership (Krizek and El-Geneidy 2007). With choice riders demonstrating greater variability in their composition, some scholars have focused on identifying sensitivity of choice riders to issues such as fare and service quality, given their alternative mobility options; by contrast, changes in usage among dependent riders have more often been considered in relation to changes in their dependency status—for example, in regard to vehicle acquisition or changes in income that make trips by another mode more affordable.

Reasons that riders give for using public transit include, as the largest category (44%), preference for non-monetary aspects of travel including convenience, time savings, environmental considerations, and avoiding traffic (Clark, 2017). The second largest category (40%) includes reasons that can be attributed to need, such as having “no car,” “no money,” or “no other transportation available.” An additional 16% of riders offer reasons related to economic considerations, including saving money on parking and gas, and, for a few, taking advantage of an employer transit subsidy.

The reasons riders give for choosing to use transit vary substantially between bus and rail modes (Clark, 2017), related to transit dependency factors. Because they tend to have higher incomes, rail riders are much less likely to state a need-based reason for using public transit than bus riders do. Rail riders tend to cite convenience, avoiding traffic, helping the environment, and preferring to save on parking costs (which may mean they have a vehicle as a transportation option or that they choose not to have a vehicle because of parking costs). Many bus riders (14%) also say they simply prefer to use the bus, or that it is more convenient than driving (12%). However, they are also more likely to offer reasons focused on need, with 15% indicating they have no car and another 15% no other transportation alternative, and 10% indicating they have no money.

One recent study, by Krizek and El-Geneidy (2007), aimed to identify the relative perceived importance of various factors on transit ridership for different transit market segments. The authors analyzed survey data obtained from Metro Transit, the largest local transit provider for the Minneapolis-St. Paul metropolitan area, from a survey of transit users conducted in 2001 and another for non-users conducted in 1999. The authors classified both transit users and non-users in the data into two groups—"captive" or in other words mode-dependent users of either a car or transit, and discretionary users (broken down into choice transit riders and "potential" transit riders).[8] They found notable similarities in the habits and preferences of choice riders (from the user analysis) and potential riders (from the non-user analysis), indicating that both these groups prize reliability, travel time, type of service, and comfort. Arguing that these population segments represent a "middle ground of potential users" for transit, the authors recommended that transit agencies target this market segment through improvements in service coverage and reliability. Considering factors deemed important by captive riders, the authors found that irregular captive riders (those who use transit occasionally and had no other alternative) reported that transit driver attitude, type of service, customer support, and safety were primary considerations. Regular captive riders, those who use transit regularly and have no other option but transit, reported that reliability, bus comfort, and safety were top considerations.

Much additional research has evaluated factors that influence transit ridership, while not directly considering transit dependency in the analysis. The research is still relevant to this report because it can shed light on factors under the control of transit agencies that influence ridership on different transit modes, findings that may be pertinent to the different project types that are eligible for California Climate Investments funding. Scholars have distinguished "internal" factors, those considered to be under the control of transit agencies, from "external" factors, not under the transit agencies' control (Krizek and El-Geneidy 2007; Iseki and Ali, 2015). Internal factors include service frequency (related to the spatial and temporal availability of service at both ends of the trip), ease of access and egress, and fare price. External factors include population change, socioeconomic and demographic change, roadway infrastructure provision, and parking and gas prices, which influence the cost of transit relative to travel by other modes. Waiting times for transit, both in-vehicle and out-of-vehicle, and travel time by transit and other modes, are other important, associated variables.

Studies evaluating factors that influence transit ridership have produced decidedly mixed results, however, reflecting substantial variation in data and methods (Iseki and Ali, 2015). A common attribute of many studies has been small sample size for relevant data, with a focus on only one or a few geographic areas, raising questions about the generalizability of findings. Meanwhile, a common distinction among studies has been a focus on different transit modes. Furthermore, "large variation" in analytical methods used in different studies has also made summary and integration of findings

[8] Auto captives were determined as survey respondents who answered positively to the statement "People like me do not ride transit" and negatively to the question "How appealing, overall, is the idea of using the bus?" Potential riders were determined as respondents (mainly commuters) who answered negatively to the statement "People like me do not ride transit" and positively to the question "How appealing, overall, is the idea of using the bus?" Captive riders were defined as those who indicated they had no other travel option but transit.

difficult across studies (Iseki and Ali, 2015). Studies have differed, for example, in which independent variables were included for analysis, leading to concerns about omitted variables bias. Some studies that included wide geographic coverage were also cross-sectional, in other words limited to only a single point in time; meanwhile other studies that employed "panel" datasets with longitudinal information about change over time were limited in geographic coverage.

A further shortcoming of most existing studies, according to Iseki and Ali (2015), was failure to account for potential endogeneity (bidirectional causality) between transit demand and supply. Levels of transit service consumption (ridership) can affect the supply of transit service, as transit agencies adjust supply within financial constraints to respond to changes in ridership; conversely, levels of transit service supplied by agencies directly influence the consumption of transit trips. Failure to account for this endogeneity may affect the accuracy of estimates of the effect of internal factors, such as level of service supplied, on ridership.

To attempt to improve on past studies on the subject, Iseki and Ali (2015) conducted longitudinal analysis using panel data for the period from 2002 to 2011 for ten major US urbanized areas (UAs), namely Boston, Chicago, Cleveland, Denver, Houston, Los Angeles, Miami, New York, San Francisco, and Seattle. The authors developed annualized data on unlinked passenger trips for bus, commuter rail, light rail, and heavy rail by agency, collected from the NTD, in order to calculate transit ridership by each mode and in aggregate for each UA. They obtained demographic and socio-economic variables from the American Community Survey, and data on federal highway miles from the Federal Highway Administration.[9]

Iseki and Ali used this dataset to conduct a fixed-effects panel data analysis with instrumental variables (IV). By using panel data, the authors could simultaneously take into account temporal and cross-sectional variation, controlling for multiple factors external to transit agencies' control but which might have influenced ridership. Fixed effects (dummy variables) were used to account for seasonal variation in ridership, annual macroeconomic change, and area-level unobserved time-invariant factors that affect ridership in each UA. Finally, instrumental variables, a technique often used to account for the simultaneous (endogenous) relationship between independent and

[9] The authors developed the following annualized data measures from the NTD: vehicle revenue hours (VRH) and vehicle revenue miles (VRM) to represent the supply of transit services, average service frequency (VRM divided by route miles), total number of employees (number of full time employees + 0.5 * number of part-time employees), fleet capacity (seating and standing) by mode, and total funds (sum of state, local and federal) available to transit agencies. They obtained the following variables from the American Community Survey 1-year estimates between 2005 and 2011: total population, number of recent immigrants, mean household income, unemployment rate, percent of households with no vehicle, number of workers that carpool, number of people in different age groups, number of people working in different industries, and college and graduate school enrollment in each UA. Annual data on federal highway miles from 2002 through 2010 were collected from the Highway Statistics Series prepared by the U.S. Department of Transportation's Federal Highway Administration.

dependent variables, were employed in this case to account for the relationship between transit supply (measured by vehicle revenue hours, or VRH) and ridership.[10]

Iseki and Ali's final model specifications were developed to be parsimonious while achieving a high "within" R-squared value, used for fixed effects models,[11] and to ensure there was no substantial collinearity among variables for each mode and specification. Because both the dependent and independent variables were measured in log form, regression coefficients can be read as elasticities; elasticities measure the percent change in the dependent variable of interest associated with a 1 percent change in the independent, explanatory variable of interest.

Results from Iseki and Ali's IV models are shown in Figure 2. Estimated elasticities (coefficients) of VRH confirm that an increase in the supply of transit service leads to an increase in ridership, with elasticities of 0.41 for bus, 0.90 for light rail and 0.58 for the aggregate transit ridership measure. The two other internal factors—fare and service frequency—generally also had expected effects on transit ridership. Fare elasticities were negative and significant for all modes, ranging from -0.44 for commuter rail to -0.14 for light rail. Meanwhile, the coefficient for service frequency had a statistically significant impact only for bus ridership, with an elasticity of 0.08. Considering external factors, the one most relevant for this report is the coefficient on percent of households with no vehicle, which was statistically significant (and negative, surprisingly) only for bus and light rail.

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[10] An initial, baseline model specification regressed the log of ridership by mode on the set of independent variables listed above, including gasoline prices. Then an IV model was employed, using as instrumental variables: total number of employees, total fleet measured as the total seating and standing capacity of transit vehicles, and total funds available for transit agencies in each UA in a particular year, combining local, state and federal funds. The authors tested these three variables to ensure they met the following necessary conditions to be considered valid instruments: first, instrument relevance, requiring that the covariance between the instruments and supply of transit service cannot be zero (in other words, requiring that the three instruments should significantly affect supply of transit services), and second, instrument exogeneity, which requires that the instruments cannot directly affect transit ridership, but do so only by affecting the supply of transit services.

[11] Within R-squared, used for an evaluation of goodness of fit for fixed effects models, measures here the proportion of variance of a dependent variable explained by variance of independent variables within each UA, taking into account variances among UAs; it measures temporal change, rather than cross-sectional differences.

Variable	Bus	CR	LR	HR w/o NY	HR w/ NY	Transit
Log of monthly gasoline price	**0.0617*** (0.0223)**	0.0640 (0.0428)	0.0253 (0.0516)	−0.0286 (0.0446)	−0.0263 (0.0403)	**0.0573** (0.0262)**
Log of fare	**−0.220*** (0.0212)**	**−0.444*** (0.0940)**	**−0.141*** (0.0355)**	**−0.263*** (0.0343)**	**−0.206*** (0.0304)**	**−0.319*** (0.0308)**
Log of vehicle revenue hours	**0.407*** (0.0519)**	0.0625 (0.152)	**0.901*** (0.0314)**	0.110 (0.0922)	0.0139 (0.0303)	**0.577*** (0.0712)**
Log of frequency of service	**0.0772*** (0.0207)**		0.0130 (0.0324)			
Log of total population	**0.811*** (0.164)**	**6.730*** (1.735)**		**−0.915* (0.467)**	**−0.693* (0.394)**	**0.845*** (0.202)**
Log of federal highway miles	**0.0670*** (0.0102)**	**−0.116*** (0.0240)**	**−0.0675*** (0.0217)**	−0.0128 (0.0245)	−0.00174 (0.0213)	0.0202 (0.0133)
Log of mean household income		1.441 (1.082)				
Unemployment rate (%)	**0.0331*** (0.00433)**		**0.0343*** (0.0108)**	**0.0349*** (0.0110)**	**0.0310*** (0.00904)**	**0.0280*** (0.00533)**
Households with no vehicle (%)	**−0.0396*** (0.0109)**		**−0.0931*** (0.0277)**			
Constant	−2.874 (2.411)	**−107.5*** (15.37)**	**6.107*** (0.321)**	**28.07*** (6.883)**	**26.24*** (6.172)**	−4.301 (2.867)
Seasonal effects (month dummies)	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Urbanized area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,126	777	840	669	789	1,132
R^2	0.504	0.662	0.839	0.462	0.430	0.237
Number of urbanized areas	10	7	9	6	7	10

NOTE: Standard errors are in parentheses. Numbers in boldface type indicate statistically significant estimated coefficients and their standard errors. Bus = unlinked bus passenger trips; CR = unlinked commuter rail passenger trips; LR = unlinked light-rail passenger trips; HR = unlinked heavy-rail passenger trips; transit = unlinked passenger trips for all modes combined; HR w/o NY = unlinked heavy-rail passenger trips without New York urbanized area; HR w/ NY = unlinked heavy-rail passenger trips with New York urbanized area. Blank cells = not applicable.
***$p < .01$, **$p < .05$, *$p < .1$.

Figure 2. Reproduction of Table 4 from Iseki and Ali (2015)

In another analysis (not shown), Iseki and Ali explicitly tested the relative influence of internal and external factors in determining transit use. In line with the elasticities shown in Figure 2, the authors determined that each of the three internal factors—fare, service, and frequency—explained more variance in transit ridership than gasoline prices after controlling for all other variables. They found that overall, internal factors played a higher relative role than external factors in explaining ridership, a finding that diverges from results from some previous studies that used cross-sectional analysis.

This finding by Iseki and Ali is a relevant and positive consideration for California Climate Investments programs, as it indicates that factors under the control of transit agencies are most influential in increasing ridership. In relation to the types of projects eligible for California Climate Investments funding, it is also useful to underscore Iseki and Ali's finding that elasticities for change in ridership associated with increases in service coverage (measured as VRH) were higher than for increases in service frequency. However, the elasticities for service coverage were statistically significant only for bus and light rail.

Section F. Recent Trends in Car Ownership and Transit Ridership in California

The Iseki and Ali study suggests that an increase in transit service coverage, such as might be made possible through a project funded by a California Climate Investments program, could significantly influence ridership. However, some other recent research on transit usage in Southern California points to a countervailing trend, in which changes in transit dependency related to shifts in car ownership patterns appear to be producing a decline in transit ridership.

In recent research conducted for the Southern California Association of Governments, Manville, Taylor, and Blumenberg (2018) examined transit usage in California and its largest metropolitan regions during the past decade, using data from the NTD. Examining the period between 2005 and 2016, they found that per capita transit ridership peaked in California in 2009, in the nation in 2008, and in the Los Angeles region in 2007. Since 2007, per capita transit use in the Los Angeles region has fallen steadily—in other words, starting before the economic recession, the rise in use of transportation network services like Lyft and Uber, and the post-2012 drop in fuel prices.

Most of California's transit use occurs in Southern California, where a majority of the state's population lives, although Northern Californians use transit more intensively, largely as a result of high ridership in San Francisco and its surrounding areas (Manville et al., 2018). From 2012 to 2016, the Los Angeles region experienced steep losses of transit ridership that accounted for (and actually exceeded) all of California's ridership losses during the same time period. Transit ridership outside the Los Angeles region, measured as the number of annual transit boardings, actually rose 20% from 2012 to 2016, largely as a result of gains made by transit systems in San Francisco. But the Los Angeles region lost 72 million annual rides, or 120% of the state's total losses, during the period in question.[12]

In looking for an explanation for this pattern, Manville and co-authors point, in particular, to patterns in vehicle ownership and access. Using Census data, the authors determined that between 2000 and 2015, households in the Los Angeles region, and especially lower-income households, dramatically increased their levels of vehicle ownership. During that period, the share of households in the region with no vehicle

[12] The authors found that Southern California's ridership declines were concentrated to a small number of transit operators. While the region's transit systems are increasingly diverse and far reaching, transit riders remain highly concentrated, with a few operators carrying most of the passengers. Four operators (LA Metro, the Orange County Transportation Authority (OCTA), the Los Angeles Department of Transportation (LA DOT), and the Santa Monica Big Blue Bus) accounted for 88% of the state's ridership losses from 2012 to 2016, and LA Metro itself for 72%. In turn, LA Metro's losses were themselves highly concentrated, with a dozen routes accounting for 38% of all the lost ridership in California during the period. Half of California's total lost ridership is accounted for by 17 LA Metro routes (14 bus and 3 rail lines) and one OCTA route.

fell by 30%, and the share of households with fewer vehicles than adults fell 14%. While from 1990 to 2000 the region had added 1.8 million people and only 456,000 household vehicles (or 0.25 vehicles per new resident), from 2000 to 2015, the region added 2.3 million people and 2.1 million household vehicles (or 0.95 vehicles per new resident).

Noting that "a defining attribute of regular transit riders is their relative lack of private vehicle access" (Manville et al., 2018, p.9), the authors found that growth in vehicle ownership in the Los Angeles region has been particularly sharp among subgroups of the population most likely to use transit, including the low-income and the foreign born from Latin America.[13] While acknowledging that vehicle ownership is not the only determinant of transit ridership, the authors contend that this factor may well have been the most important in explaining ridership losses. They make this case in part by discounting other possible explanations, including shifts in transit service provision and fare levels, as less persuasive. They also corroborate their case by constructing and comparing a model of predicted change in transit ridership that includes only changes in socioeconomic attributes to a model that also accounts for changes in vehicle access.

The Los Angeles region made heavy investments in rail transit in recent decades, adding over 100 miles of light and heavy rail, and over 530 miles of commuter rail since 1990 (Manville et al., 2018). In spite of these investments, however, the region's transit ridership reached its postwar peak in absolute terms in 1985, and has declined in per capita terms ever since. Due to declining patronage, between 2005 and 2016, transit productivity—measured as passenger boardings per VRH—fell 5% in California and 14% in the Los Angeles region (Manville et al., 2018).
In spite of investments in rail, bus travel has remained the workhorse of public transit in the Los Angeles region, comprising 86% of transit trips. Examining the routes that lost ridership between 2012 and 2016, Manville and co-authors found that they included both bus and rail. The transit decline thus spanned modes, and was not simply a story of buses falling behind surging rail transit travel, according to the authors. Major bus and rail routes running into the heart of Los Angeles—the sort of routes where transit use has traditionally been strongest—were most likely to lose riders.

Moreover, ridership fell even on routes that maintained excellent on-time records. According to Manville and co-authors, this combination of circumstances suggests that service quantity and reliability were not large factors in explaining falling transit use. Transit fare prices also fail to provide an adequate explanation for falling ridership, because the inflation-adjusted average fare paid per mile of transit travel between

[13] Among foreign-born residents, zero-vehicle households declined by 42%, and those with fewer vehicles than adults by 22%. Among foreign-born households from Mexico, the share of households without vehicles declined even more sharply, by 66%, while households with more adults than vehicles dropped 27%.

2002 and 2016 was lower in Southern California than in the rest of the state and the nation, and was quite flat over time.

The authors also discount explanations for falling transit ridership linked to gas price shifts and rising use of services of transportation network companies (TNCs) like Lyft and Uber. They note that fuel prices fell substantially after 2012, which could align with falling transit ridership during the period, as riders may have switched to driving as gas became more affordable. However, overall, the timing of transit's decline is not conducive to a fuel price explanation, according to the authors. Per capita transit use in Southern California has been falling since 2007, even during periods of sharply rising gas prices. Regarding use of TNCs, the authors explain that while adequate data is very hard to obtain to measure effects on transit use, some evidence indicates that TNC trips are probably not replacing large numbers of transit trips, as the typical TNC user does not resemble the typical transit rider, the typical TNC trip does not occur when and where most transit trips occur, and most TNC users report no change in their travel by other mode. Furthermore, TNCs began operating in Southern California in 2009, they explain, and did not begin serving people in large numbers until 2012—after the point when per capita transit ridership began falling (in 2007).

As another alternative explanation, Manville and co-authors considered the possibility that neighborhood change has altered transit ridership. Given that transit is heavily-supplied in a small proportion of places, and heavily used by a small proportion of people, sociodemographic changes in neighborhoods with high transit quality and accessibility could alter transit use. The authors found some evidence consistent with the idea that neighborhood change has been associated with lower transit use, as areas heavily populated with transit commuters in the year 2000 became, over the next 15 years, slightly less poor, and significantly less foreign born. Perhaps more important, according to the authors, is the finding that the share of households without vehicles in these neighborhoods also fell notably. However, the authors explain that while these factors show some evidence of replacement of the transit-using populace by people more likely to drive, the evidence is currently insufficient to declare neighborhood change a large culprit in explaining falling transit ridership.

Manville and co-authors reinforce their claim that vehicle access provides the most likely explanation for falling transit ridership by constructing models to compare predicted outcomes for change in transit ridership from 2000 to 2015, first, considering only changes predicted to occur in response to shifts in socioeconomic attributes other than vehicle ownership, and second, also incorporating shifts in vehicle access into the model. The authors estimated a multivariate regression model using data from the CHTS, to predict the effect of multiple demographic and socioeconomic factors, including sex, nativity, income, and vehicle ownership, on the propensity to use transit (measured as total number of unlinked trips).[14] Then, using

[14] Manville and co-authors employed a zero-inflated negative binomial regression for this analysis. A negative binomial regression is a standard tool for analyzing "over-dispersed" count data, and the

2000, 2010 and 2015 Census IPUMS microdata, the authors applied the parameters derived from the CHTS model, to predict how transit use would have changed based on observed changes in the same selected characteristics across the Census years. The method assumes that changes in transit use from 2000 to 2015 were driven primarily by changes in the composition of the population rather than changes in the propensity of different groups to use transit. Results from this exercise demonstrated that when using parameters from all factors except vehicle ownership, a decline in transit trips was not predicted over time. However, when the parameter for ownership was added in, very different predictive results were obtained, indicating a steep fall in transit ridership.

The authors conclude by noting that reasons for the rise in vehicle ownership by traditional transit users remain somewhat unclear. One factor they point to is composition of the foreign born. The share of the overall regional population comprised by the foreign born dropped slightly between 2000 and 2015, mainly reflecting the trend in Los Angeles County. The composition of immigrants, however, changed more substantially during the same period, as the share of the foreign-born from Asia rose 23%, while the share from Central America fell 10%, and the share from Mexico fell 13%. Because evidence from the US Census indicates that immigrants from Mexico and Central America are less likely to have automobiles and drive than immigrants from other origin countries, this shift could contribute to rising auto use, especially among the foreign born. Evidence also indicates that more immigrants are likely to own vehicles earlier after arrival.

Considering economic factors, the authors found no simple economic explanation for the observed shifts in vehicle ownership. Census data suggests that newer waves of immigrants in the Los Angeles region have been slightly poorer than the cohorts that came before them (in 2000 average incomes of immigrants that had arrived since 1990 were slightly higher than average incomes of immigrants in 2010 who had arrived after 2000). Vehicle ownership growth occurred across all income groups, for both the foreign-born and the native-born.

Manville and co-authors then consider a few other factors that might help explain the rise in vehicle ownership, including easier access to credit in recent years for purchasing automobiles. However, in summary, they conclude that more research is needed to fully investigate and understand the trend. They point to research (e.g., by Giuliano, 2005) indicating that compared to Americans at large, the poor use transit more but like it less. In Southern California, acquiring an automobile makes life easier along multiple dimensions, such as by increasing access to jobs and educational institutions, among other opportunities (Kawabata and Shen, 2006). The typical low-income rider wants to gain access to an automobile, while the typical driver might view transit positively but demonstrates little interest in using it (Manville and Cummins, 2015).

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zero-inflation corrects for bias that might otherwise be introduced when the value of the dependent variable is frequently zero, as it is with personal transit trips.

These facts, coupled with the falling transit ridership of recent years, raise questions about transit's future, according to Manville and co-authors. For transit agencies to protect their fiscal health while also increasing social welfare, they may need to focus on convincing the vast majority of people who never use transit to begin riding occasionally instead of driving, rather than focus on trying to keep the transit-dependent from shifting to greater automobile use, the authors contend.

This task aligns with goals of state agencies such as CARB to encourage transit use for non-economic reasons, such as environmental benefits. The question is whether the prospect could also align with economic realities. In a few parts of the state, transit competes successfully with cars, even for the affluent traveler. In northeastern San Francisco, for example, the combination of heavy congestion, high tolls, and scarce and expensive parking make the price of owning and operating a vehicle high, encouraging even the affluent to ride transit (Manville et al., 2018). Yet few parts of Southern California challenge drivers in this way, according to Manville and co-authors, because while congestion is severe, parking is abundant and often inexpensive, and low-to-moderate densities make transit less able to effectively link many places. As market interest in infill development continues to reshape many urban neighborhoods in California in coming years, an unresolved question remains whether enough density can be built near transit to reach a "tipping point" such as in San Francisco, where transit becomes a viable and attractive alternative to driving for all potential transit user groups.

Section G. Conclusions from Research Review

Summarizing the findings from research discussed in this report, the interplay of needs, preferences, and constraints among different segments of the transit-using public is a key concern for transit proponents to consider in coming years, as infill development reshapes the contours of many urban, transit-friendly neighborhoods, and as car ownership patterns alter transit dependency among traditionally transit-using groups. On the one hand, the findings from the carefully constructed Iseki and Ali study indicate that "internal" factors under the control of transit agencies—especially including transit service coverage and fare price—are predominant influences on ridership, especially for bus and light rail. Although transit dependency was also statistically significant in Iseki and Ali's models for bus and light rail, the elasticity was considerably smaller than for service coverage (and surprisingly, had a negative sign on the coefficient, after controlling for all other variables in the equation). This finding bodes well for programs, like California Climate Investments programs, that intend to encourage ridership through targeted support.

On the other hand, the Manville study seems to indicate an entirely different conclusion, namely that "internal" factors do not serve to adequately explain patterns of falling transit ridership in the Los Angeles region. Manville and co-authors did not construct the same sort of longitudinal data analysis as Iseki and Ali, to control for multiple variables across time and geography. Nevertheless, their findings provide strong "circumstantial" evidence that shifts in transit dependency, mediated through car ownership, may be exerting an influence on ridership at least in the Los Angeles area. The Manville study suggests that CARB might want to consider developing regionally specific "A" factors, which would be possible using the CHTS dataset (noting, however, that Manville and co-authors traced the steep decline in transit ridership in Southern California, diverging from the pattern in Northern California, starting in 2012, the same year that the CHTS survey was conducted).

At the intersection of the seemingly diametrically opposed findings from the studies discussed in this report, a few conclusions might be drawn: first, that transit dependency remains a key variable in determining ridership (based on the Manville findings, at least); second, that conditions of dependency are changing due to shifting patterns of vehicle access, at least in Southern California; third, that transit usage may also be changing due to neighborhood change; and fourth, that this combination of factors suggests that patterns of transit use among choice riders and "potential" riders may become increasingly important as determinants of ridership in coming years, even as the needs of core transit-dependent users must also be addressed.

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Appendix A

Table A1. Length of average trip statewide by agency, from 2016 National Transit Database

Agency	Mode	Average trip length (miles)*
Access Services	DR	11.88
Access Services	DT	14.99
Alameda-Contra Costa Transit District	CB	14.38
Alameda-Contra Costa Transit District	DR	10.23
Alameda-Contra Costa Transit District	MB	3.55
Altamont Corridor Express	CR	43.00
Anaheim Transportation Network	MB	1.98
Antelope Valley Transit Authority	CB	62.54
Antelope Valley Transit Authority	DR	8.79
Antelope Valley Transit Authority	MB	14.91
Butte County Association of Governments	DR	3.82
Butte County Association of Governments	MB	5.78
California Vanpool Authority	VP	44.34
Central Contra Costa Transit Authority	DR	10.48
Central Contra Costa Transit Authority	MB	4.44
City of Commerce Municipal Buslines	DR	7.86
City of Commerce Municipal Buslines	MB	3.84
City of Elk Grove	CB	13.64
City of Elk Grove	DR	7.59
City of Elk Grove	MB	3.99
City of Fairfield - Fairfield and Suisun Transit	CB	17.86
City of Fairfield - Fairfield and Suisun Transit	DR	9.58
City of Fairfield - Fairfield and Suisun Transit	MB	2.64
City of Gardena Transportation Department	DR	3.53
City of Gardena Transportation Department	MB	3.59
City of Glendale	DR	5.16
City of Glendale	MB	2.18
City of La Mirada Transit	DR	3.00
City of Lodi - Transit Division	DR	2.65
City of Lodi - Transit Division	MB	2.81
City of Los Angeles Department of Transportation	CB	16.88
City of Los Angeles Department of Transportation	DR	4.78
City of Los Angeles Department of Transportation	DT	2.39
City of Los Angeles Department of Transportation	MB	1.36
City of Petaluma	DR	3.26
City of Petaluma	MB	2.12
City of Redondo Beach - Beach Cities Transit	DR	4.36
City of Redondo Beach - Beach Cities Transit	MB	3.90
City of Riverside Special Transportation	DR	7.49
City of San Luis Obispo	MB	2.90

City of Santa Rosa	DR	5.42
City of Santa Rosa	MB	3.83
City of Tulare	DR	6.26
City of Tulare	MB	4.23
City of Turlock	DR	7.29
City of Turlock	MB	3.28
City of Visalia - Visalia City Coach	CB	45.00
City of Visalia - Visalia City Coach	DR	7.85
City of Visalia - Visalia City Coach	MB	5.58
Claremont Dial-a-Ride	DR	4.09
Claremont Dial-a-Ride	DT	2.27
Culver City Municipal Bus Lines	DR	2.26
Culver City Municipal Bus Lines	MB	3.64
El Dorado County Transit Authority	CB	51.94
El Dorado County Transit Authority	DR	11.47
Foothill Transit	MB	8.21
Fresno Area Express	DR	7.29
Fresno Area Express	MB	2.61
Gold Coast Transit	DR	7.23
Gold Coast Transit	MB	4.10
Golden Empire Transit District	DR	7.08
Golden Empire Transit District	MB	3.61
Golden Gate Bridge, Highway and Transportation District	DR	12.42
Golden Gate Bridge, Highway and Transportation District	FB	10.95
Golden Gate Bridge, Highway and Transportation District	MB	18.12
Imperial County Transportation Commission	DR	17.27
Imperial County Transportation Commission	MB	10.35
Kings County Area Public Transit Agency	DR	3.53
Kings County Area Public Transit Agency	MB	5.53
Laguna Beach Municipal Transit	MB	2.18
Livermore / Amador Valley Transit Authority	DR	10.18
Livermore / Amador Valley Transit Authority	MB	4.96
Long Beach Transit	DR	4.58
Long Beach Transit	MB	3.22
Los Angeles County Metropolitan Transportation Authority: Metro	HR	4.88
Los Angeles County Metropolitan Transportation Authority: Metro	LR	6.88
Los Angeles County Metropolitan Transportation Authority: Metro	MB	4.11
Los Angeles County Metropolitan Transportation Authority: Metro	RB	6.44
Los Angeles County Metropolitan Transportation Authority: Metro	VP	45.42
Marin County Transit District	DR	8.24
Marin County Transit District	MB	4.06
Modesto Area Express	DR	7.14
Modesto Area Express	DT	4.93
Modesto Area Express	MB	3.38

Montebello Bus Lines	DT	2.09
Montebello Bus Lines	MB	3.24
Monterey-Salinas Transit	CB	40.42
Monterey-Salinas Transit	DR	12.65
Monterey-Salinas Transit	MB	5.76
Napa Valley Transportation Authority	CB	21.58
Napa Valley Transportation Authority	DR	7.32
Napa Valley Transportation Authority	MB	7.45
North County Transit District	CR	28.11
North County Transit District	DR	13.22
North County Transit District	MB	5.03
North County Transit District	YR	8.71
Norwalk Transit System	DR	3.58
Norwalk Transit System	MB	3.35
Omnitrans	DR	14.24
Omnitrans	MB	5.19
Orange County Transportation Authority	CB	20.66
Orange County Transportation Authority	DR	11.29
Orange County Transportation Authority	DT	3.02
Orange County Transportation Authority	MB	3.53
Orange County Transportation Authority	VP	34.57
Paratransit, Inc.	DR	9.51
Paratransit, Inc.	DT	7.91
Peninsula Corridor Joint Powers Board dba: Caltrain	CR	26.60
Peninsula Corridor Joint Powers Board dba: Caltrain	MB	3.47
Placer County Department of Public Works and Facilities	CB	21.99
Placer County Department of Public Works and Facilities	DR	3.82
Placer County Department of Public Works and Facilities	DT	13.86
Placer County Department of Public Works and Facilities	MB	7.81
Placer County Department of Public Works and Facilities	VP	39.74
Pomona Valley Transportation Authority	DR	5.02
Pomona Valley Transportation Authority	DT	4.89
Redding Area Bus Authority	DR	9.06
Redding Area Bus Authority	MB	6.50
Riverside Transit Agency	CB	20.56
Riverside Transit Agency	DR	12.54
Riverside Transit Agency	DT	16.56
Riverside Transit Agency	MB	6.33
Sacramento Regional Transit District	DR	2.66
Sacramento Regional Transit District	LR	5.66
Sacramento Regional Transit District	MB	3.63
San Diego Association of Governments	VP	48.79
San Diego Metropolitan Transit System	CB	23.69
San Diego Metropolitan Transit System	DR	9.98
San Diego Metropolitan Transit System	LR	5.56
San Diego Metropolitan Transit System	MB	3.84
San Francisco Bay Area Rapid Transit District	HR	13.50
San Francisco Bay Area Rapid Transit District	MG	3.20
San Francisco Bay Area Water Emergency Transportation Authority	FB	14.85

San Francisco Municipal Railway	CC	1.25
San Francisco Municipal Railway	DR	6.03
San Francisco Municipal Railway	LR	2.72
San Francisco Municipal Railway	MB	2.26
San Francisco Municipal Railway	SR	1.48
San Francisco Municipal Railway	TB	1.50
San Joaquin Regional Transit District	CB	44.30
San Joaquin Regional Transit District	DR	11.30
San Joaquin Regional Transit District	DT	6.48
San Joaquin Regional Transit District	MB	3.64
San Luis Obispo Regional Transit Authority	DR	7.95
San Luis Obispo Regional Transit Authority	MB	12.43
San Mateo County Transit District	DR	8.45
San Mateo County Transit District	DT	13.11
San Mateo County Transit District	MB	4.69
Santa Barbara Metropolitan Transit District	MB	4.59
Santa Clara Valley Transportation Authority	DR	10.12
Santa Clara Valley Transportation Authority	LR	5.10
Santa Clara Valley Transportation Authority	MB	5.88
Santa Clarita Transit	CB	19.28
Santa Clarita Transit	DR	8.07
Santa Clarita Transit	MB	4.38
Santa Cruz Metropolitan Transit District	CB	31.21
Santa Cruz Metropolitan Transit District	DR	6.70
Santa Cruz Metropolitan Transit District	DT	6.70
Santa Cruz Metropolitan Transit District	MB	5.34
Santa Maria Area Transit	DR	5.48
Santa Maria Area Transit	MB	4.37
Santa Monica's Big Blue Bus	DR	2.49
Santa Monica's Big Blue Bus	MB	4.23
Solano County Transit	CB	12.72
Solano County Transit	DR	6.10
Solano County Transit	MB	3.06
Sonoma County Transit	DR	12.52
Sonoma County Transit	MB	8.37
Southern California Regional Rail Authority: Metrolink	CR	30.93
SunLine Transit Agency	DR	11.94
SunLine Transit Agency	MB	7.14
The Eastern Contra Costa Transit Authority	DR	6.26
The Eastern Contra Costa Transit Authority	MB	7.26
Torrance Transit System	DT	6.17
Torrance Transit System	MB	4.40
Transit Joint Powers Authority for Merced County	DR	6.05
Transit Joint Powers Authority for Merced County	MB	6.31
Unitrans - City of Davis/ASUCD	MB	2.15
Ventura Intercity Service Transit Authority	CB	11.60
Ventura Intercity Service Transit Authority	DR	4.27
Ventura Intercity Service Transit Authority	MB	4.40

Victor Valley Transit Authority	CB	51.18
Victor Valley Transit Authority	DR	13.83
Victor Valley Transit Authority	MB	6.23
Victor Valley Transit Authority	VP	47.11
Western Contra Costa Transit Authority	CB	23.19
Western Contra Costa Transit Authority	DR	7.47
Western Contra Costa Transit Authority	MB	7.43
Yolo County Transportation District	DR	11.05
Yolo County Transportation District	MB	10.39
Yuba-Sutter Transit Authority	CB	38.82
Yuba-Sutter Transit Authority	DR	6.90
Yuba-Sutter Transit Authority	MB	2.99

*Calculated by dividing passenger miles traveled by unlinked passenger trips.