

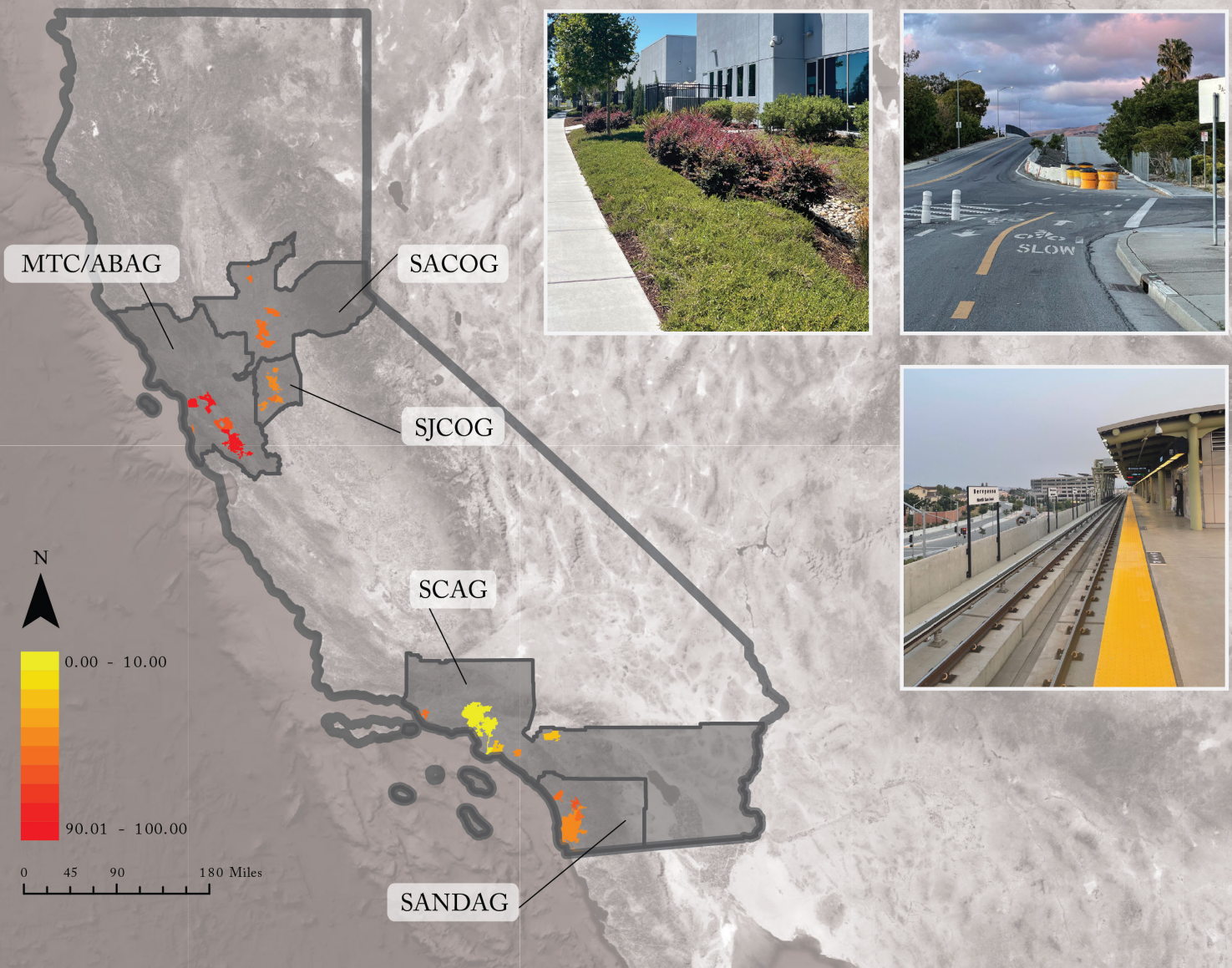
Fragmented or Aligned Climate Action: Assessing Linkages Between Regional and Local Planning Efforts to Meet Transportation Greenhouse Gas Emissions Reduction Targets

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All Policy Alignment Percentile Score



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Executive Summary

Introduction

California's Sustainable Communities and Climate Protection Act of 2008, or Senate Bill (SB) 375, is a first-of-its-kind law that recognizes the key role transportation and land use decisions play in addressing climate change. Under SB 375, each of California's 18 regional Metropolitan Planning Organizations (MPOs) is responsible for developing a Sustainable Communities Strategy (SCS): a regional transportation and land use vision that demonstrates how the region, in partnership with its local member agencies, plans to meet the GHG emission reduction targets set by California Air Resources Board (CARB). Lessons learned from SB 375's implementation can help state, regional, and local governments encourage better transportation and planning decisions to combat climate change. Despite extensive state efforts in designing climate policies, a progress report published in June 2022 indicates that California is still not reducing GHG emissions from transportation, and particularly personal vehicle travel, enough to meet SB 375's goals.

A key challenge to meeting California's ambitious emissions reduction goals is how well regional and local climate policies align. Since the strategies outlined in the SCS often fall under the jurisdiction of local agencies, local officials ultimately determine whether and how the provisions of SB 375 are implemented. Local jurisdictions are not required to develop a Climate Action Plan (CAP), although they are encouraged and supported by the state and regional agencies to do so. While the General Plan (GP) remains the only comprehensive and binding municipal plan, many jurisdictions choose to develop a CAP and funnel the GHG reduction efforts through climate action planning. It is important to note that the SCS does not supersede a local climate action plan (CAP), nor does it require that local plans and policies be necessarily consistent with the SCS. This can result in a potential misalignment between regional SCSs and local CAPs. Given the magnitude of the disruptive climate impacts that the state already is facing, many climate-concerned Californians raise important questions:

- 1) Are the transportation and land use strategies and targets in SCS plans reflected in the local plans to build sustainable communities?
- 2) Does the alignment of regional and local transportation and land-use strategies mitigate GHG emissions through vehicle trip reduction?
- 3) How different are the effects of independent local action and alignment of local and regional actions on vehicle trip reduction?

Study Methods

The authors used a two-phased mixed-method approach to examine the alignment of local and regional climate strategies and their impact on vehicle trip reduction. The first phase involved a

qualitative content-analysis of local CAPs and regional SCSs representing the five most populous regions in California. Within each region, listed in Table 1 on page 6, five cities were selected for a specific focus. The city list is displayed in Table 2, page 8. The sample included both larger and smaller cities and communities with a wide range of transportation needs (e.g., high or low commute range) and climate planning efforts (e.g., cities with or without a CAP). The content analysis identified and categorized the transportation and land use (TLU) strategies. The content analysis results were used in alignment operationalization, which included measuring the alignment level between local and regional plans for TLU strategies and using weights that quantify such alignments' impact on vehicle-trip reduction over time. These measures lead to an optimal estimation of alignment scores.

Key Findings

Major findings can be summarized as follows: (1) The patterns of local and regional climate policy are diverse across the state, but poor alignment is not necessarily a sign of limited climate action at the local level; (2) Active transportation strategies are the most commonly found strategies in regional and municipal climate action plans that effectively reduce vehicle trips; (3) The analyzed cities and regions consistently plan for densification and land use diversity; (4) Policies that aim to improve mass transit networks and ridership are the most effective in reducing vehicle trips, though the scope and types of these policies differ between larger and smaller cities; (5) Well-aligned regional and local level climate-friendly infrastructure appear to have the most significant impact on vehicle-trip reduction, on average a 7% decrease in vehicle trips; (6) Many local level strategies alone, such as strategies for goods movement, urban forest strategies, parking requirements, and education and outreach programs, are effective in vehicle-trip reduction; (7) Built-environmental factors, such as density, land use diversity, walkability, and a strong transit system are all significant indicators of increase in non-auto commute; (8) Job-housing balance strategies should be coupled with adequate transit access to effectively impact vehicle trips; otherwise, vehicle trips will increase as the population increases.

Policy Takeaway

A major takeaway from this research is that although local and regional climate policy alignment can be crucial for successfully reducing vehicle trips, local action is equally important. While there are established best practices for climate action planning, there is no one-size-fits-all approach to reducing transportation emissions. Regional SCSs often use best practices and analysis of regional context to develop climate strategies, while municipalities develop and implement CAPs to address local needs. Some cities have a longer history of climate planning, and, by extension, the capacity to take innovative action to address transportation emissions and even lead regional climate efforts. Others are just starting the process of developing a CAP and require more technical and financial support from the regional and state governments. The results of this research also show that while alignment of regional and local policies is important in some areas, local action can be more effective in others. Specifically, strategies to engage communities in climate planning or policies to

address local problems, such as parking, can be more successful at the local level. Therefore, the State of California should support both local and regional action to address transportation emissions.

1. Introduction

The effects of climate change impact the everyday lives of Californians in far-reaching ways. From record temperatures to rising sea levels and proliferating wildfires across the state, climate change affects the health and well-being of our communities. There is a sense of urgency directed toward developing new approaches and evaluating California’s current ways of addressing climate change.

The California Air Resources Board (CARB) published a progress report in June 2022 indicating that California is still not reducing GHG emissions from transportation, and particularly personal vehicle travel, enough to meet SB 375 goals.¹ Given the magnitude of the disruptive climate impacts that the state currently faces, many Californians raise an important question: As a national leader in climate policy, what are the gaps in our current climate planning approaches?

The biggest challenge to meeting California’s ambitious emissions reduction goals lies in the transportation sector, which has been identified as the most significant contributor to GHG emissions in California, and transportation emissions have proven challenging to tackle. Recognizing the critical role of local and regional transportation and land-use decisions in achieving GHG emissions targets, SB 375 established a “bottom-up” approach,² where each of California’s 18 regional Metropolitan Planning Organizations (MPOs) is responsible for developing a Sustainable Communities Strategy (SCS): a regional transportation and land use vision that demonstrates how the region, in partnership with its local member agencies, plans to meet the GHG emission reduction targets set by CARB. Nonetheless, since the strategies outlined in the SCS often fall under the jurisdiction of local agencies, local officials ultimately determine if and how the provisions of SB 375 are implemented.

Moreover, jurisdictions are not required to develop a Climate Action Plan (CAP), although they are encouraged and supported by the state and regional agencies through funding and technical assistance to do so. Although the General Plan (GP) remains the only comprehensive and binding municipal plan, many jurisdictions choose to develop a CAP and funnel the GHG reduction efforts through climate action planning. It is important to note that the SCS does not supersede a local climate action plan (CAP), nor does it necessarily require that local plans and policies be consistent with the SCS. A possible lack of alignment between local plans and regional SCS might be one reason California is not making sufficient progress in its GHG emissions mitigation efforts.

Current literature offers limited and conflicting evidence for how regional plans promote local voluntary adoption of sustainable transportation and development strategies. For example, a longitudinal analysis of regional and city plans in the Denver metropolitan area suggests that although local development is still largely driven by local views and market forces, MPOs have been generally successful in encouraging mixed-use and high-density development that can help reduce Vehicle Miles Traveled (VMT) and GHG emissions.³ Yet, another study analyzed the effect of regional planning on local development patterns in the Sacramento region and found that

neighborhoods meeting principles of the regional “Blueprint” did not necessarily receive the most new residential development over the years; ironically, highly rated neighborhoods received less residential development after adopting the regional plan.⁴ Additionally, the literature offers few insights into the extent to which regional strategies to reduce GHG emissions have been reflected in local plans. A 2017 report published by the National Institute for Transportation and Communities (NITC) examined how regional transportation plans developed by MPOs in California and Oregon responded to state planning mandates to reduce GHG emissions from transportation and found an increased focus on climate change as a result of establishing regional GHG emissions reduction targets.⁵ However, the report did not assess the impact of state mandates or regional plans on relevant local plans. Another recent study emphasized the importance of systematically evaluating how MPOs across the state “nudge” local governments to implement more compact and less automobile-focused development to meet California’s GHG emissions targets.⁶ More specifically, the findings of this research indicate that individual MPOs generally conduct a limited evaluation of how local land use practices and built environment changes align with SB 375 and, subsequently, the regional SCS. As a result, there is a need for a systematic assessment of the alignment between regional SCSs and local CAPs across California.

This report fills in the knowledge gap in the literature by systematically examining the level of alignment between regional and local efforts to reduce GHG emissions and assessing how the alignment (or lack thereof) of common GHG emissions reduction strategies at regional and local levels affects vehicle trip reduction. Our research builds upon the rich body of literature focusing on factors affecting vehicle trips, such as transportation and land use characteristics of an area (i.e., density, land-use mix, job-housing balance, distance to transit, etc.), and policies and programs designed to lessen driving (i.e., employer-based trip reduction, transit service incentives, etc.).⁷ However, no other study has examined how the alignment between regional and local policies designed to reduce GHG emissions has an impact on vehicle trips. For California to reach its ambitious GHG emissions goal, it is crucial to have a clear understanding of whether and how regional SCSs flow down into local plans and what impact alignment or fragmentation of GHG emissions reduction strategies at regional and local levels might have on vehicle trip reduction.

Over the past decade, considerable attention has been paid in the literature to the potentials and barriers of local climate action planning,⁸ and less emphasis has been placed on the synergies between local and regional climate planning efforts. A recent study focusing on the impact of Senate Bill (SB) 375 on local climate change planning suggested that the lack of a mandate for local jurisdictions to develop consistent strategies with the SCS can result in a free-rider problem for regional outcomes.⁹ Over time, we might see a patchwork of climate policies at local and regional levels with some cities meeting or exceeding regional targets and others failing to develop a CAP or to take any climate action at all. The state will then confront questions of whether the regional umbrella is even necessary, if alignment of local policies with SCS cannot be enforced, and especially if local action can be proved effective.

This research aims to fill in some of these key gaps in knowledge by exploring three research questions:

Are the transportation and land-use strategies and targets in SCS plans reflected in the local jurisdictions' plans (i.e., are they "flowing down")?

Does the alignment (or lack thereof) of regional and local transportation and land-use strategies mitigate GHG emissions through vehicle trip reduction?

How different are the effects of independent local action and alignment of local and regional actions on vehicle trip reduction?

To address these questions, the team identified five MPOs, 20 municipalities that developed a CAP (five per region), and an additional city in each region that has not yet developed a CAP. The authors collected and analyzed the content of the SCSs and CAPs. The content analysis focused on identifying and categorizing the transportation and land-use strategies. The results were used in alignment operationalization, which included measuring the level of alignment between TLU strategies resulting in an alignment score and examining the relationship between the alignment of these strategies, local level actions, and vehicle trip reduction over time.

The remainder of this report is organized into the following three chapters. Chapter 2 includes the content analysis method and the results of the five SCSs and 20 local CAPs. Chapter 3 provides the alignment operationalization methodology and the discussion of findings. Finally, in Chapter 4, the authors synthesize and discuss the key findings and conclusions and provide policy recommendations.

2. Content Analysis of the Regional (SCSs) and Local Climate Action Plans (CAPs)

This chapter describes the methodology and results from content analysis of the regional Sustainable Communities Strategies (SCS) and local climate action plans (CAPs). The goal is to determine the extent to which regional SCSs developed by MPOs align with local plans.

2.1 Sample

The research team identified the five most populous regions in California that represent both larger and smaller cities, advantaged and disadvantaged communities, and a wide range of transportation needs (e.g., high or low commute range). The authors first reviewed and analyzed regional SCSs developed by MPOs in these five regions. Specifically, the team reviewed SCS plans developed by the MPOs displayed in Table 1 below.

Table 1. Selected MPOs and Reviewed SCSs List

| MPO | MPO | SCS | Date adopted |
|--|----------|--|-----------------------------|
| Metropolitan Transportation Commission / Association of Bay Area Governments | MTC/ABAG | Plan Bay Area 2050 | Draft released May 26, 2021 |
| Sacramento Area Council of Governments | SACOG | 2020 Metropolitan Transportation Plan/Sustainable Community Strategy | Nov. 18, 2018 |
| San Diego Association of Governments | SANDAG | San Diego FORWARD - the 2021 regional plan | Draft released May 2021 |
| San Joaquin Council of Governments | SJCOG | 2018 Metropolitan Transportation Plan/Sustainable Community Strategy | June, 2018 |

Within each region, five cities were selected for specific focus. The authors ensured that a variety of communities were involved in the study to represent the wide range of climate action and transportation needs in the State of California. The sample of 25 cities listed in Table 2 includes five cities per selected region, of which one city per region has not yet developed a CAP. Additionally, city population and location were used as criteria in selecting the cities. The research team included the most populous cities, as well as cities from the mid-size and smaller-size ranges. Geographically, the team intended to select city locations dispersed within the MPO regions.

Table 2. Selected Cities, their Population and Share in Regional Population.

| City | Developed a CAP | Population | MPO | Total Population of selected cities | Total MPO Population | Selected cities population percentage in MPO | | | | |
|---------------|-----------------|------------|----------|-------------------------------------|----------------------|--|--------|-----------|-----------|--------|
| Stockton | ✓ | 299,722 | SJCOG | 540,524 | 562,645 | 96.07% | | | | |
| Tracy | ✓ | 85,284 | | | | | | | | |
| Manteca | ✓ | 72,251 | | | | | | | | |
| Lodi | ✓ | 63,589 | | | | | | | | |
| Lathrop | | 19,678 | | | | | | | | |
| Los Angeles | ✓ | 3,900,794 | SCAG | 5,224,129 | 16,553,611 | 31.56% | | | | |
| Long Beach | ✓ | 470,237 | | | | | | | | |
| Santa Ana | ✓ | 333,268 | | | | | | | | |
| Riverside | ✓ | 316,335 | | | | | | | | |
| Oxnard | | 203,495 | | | | | | | | |
| San Diego | ✓ | 1,359,791 | | | | | SANDAG | 1,833,787 | 2,721,138 | 67.39% |
| Oceanside | ✓ | 173,050 | | | | | | | | |
| Escondido | ✓ | 149,079 | | | | | | | | |
| El Cajon | ✓ | 102,383 | | | | | | | | |
| Poway | | 49,484 | | | | | | | | |
| Sacramento | ✓ | 480,566 | SACOG | 842,482 | 1,430,549 | 58.89% | | | | |
| Elk Grove | ✓ | 161,084 | | | | | | | | |
| Roseville | ✓ | 126,327 | | | | | | | | |
| Yuba City | ✓ | 66,038 | | | | | | | | |
| Live Oak | | 8,467 | | | | | | | | |
| San Jose | ✓ | 1,000,860 | MTC/ABAG | 2,486,969 | 6,731,384 | 36.95% | | | | |
| San Francisco | ✓ | 840,763 | | | | | | | | |
| Oakland | ✓ | 408,073 | | | | | | | | |
| Fremont | ✓ | 225,221 | | | | | | | | |
| Half Moon Bay | | 12,052 | | | | | | | | |

2.2 Developing a Framework

The analysis approach consisted of three stages. In the first stage, the research team developed a framework for capturing Transportation and Land Use (TLU) policy efforts aiming to reduce GHG emissions. In this task, the authors reviewed climate planning literature and the SCSs and CAPs gathered through the data collection process. Through iterative observations, classification, and keyword searches, the authors developed variables to be included in the quantitative phase of the analysis, described in Chapter 3. The authors also sought feedback from CARB to finalize and validate the categories and subcategories of transportation strategies to reduce GHG emissions. The variables and the keywords are displayed in Table 3.

Table 3. Content Analysis Variables and Search Keywords by Category

| Category | Variable | Keywords |
|----------------------|---|--|
| Transportation | Bicycle | bicycle; bike |
| | Pedestrian | pedestrian |
| | Complete Streets | complete street; multi modal; supports multiple modes |
| | Mass Transit | transit |
| | Electric Vehicle | EV; electric; vehicle |
| | Ride-sharing | car; shar[ing]; hail[ing]; rideshar[ing] |
| | Low-carbon / Alternative Fuel Vehicle | EV; hybrid; alternative |
| | Autonomous Vehicles | autonomous; self |
| | Climate-friendly infrastructure | pavement; pave; friendly; permeable; lighting; infra-structure |
| | Vehicle Idling | idl[ing] |
| Land-use | Goods movement | goods; freight |
| | Transit Oriented Development | TOD; orient[ed] |
| | Infill Development | infill; density zoning graduated |
| | ADU Development Program | ADU; accessory; [in -] law [units]; flat |
| | Housing Development Near Activity Centers | center; activity; mix |
| | Housing Affordability and Jobs-Housing Balance | balance; job; affordable |
| | Preserve / Restore Open Space, Farmland, Natural Beauty, and Critical Environmental Areas | open space; farm; beauty; critical; environ[ment]; habitat |
| | Urban Growth Boundary | urban g[rowth]; growth b[oundary] |
| | Parking Requirements | parking; curb |
| | Urban Forest | forest; greening |
| TDM | Port Policies | sea; maritime |
| | TDM | system management; TDM; TSM |
| Cross-cutting issues | Education and Outreach | education; outreach |
| | Regional Collaboration | region[al] collab[oration] |
| | Community Involvement and Outreach Equity | CIO; community; outreach equity; frontline [communities]; climate [equity] |

To determine whether the regional or local plan has a strategy, the authors defined the strategy in the context of SCSs and CAPs as a long-range public policy that can be implemented at any governmental level. The strategy can involve various actors, such as the government or private and nonprofit organizations, but is not necessarily of a mandatory or legislative nature.

In the analyzed plans, the strategies are most often identified as mitigation strategies focusing on reducing GHG emissions (as opposed to adaptation strategies to help communities cope with climate impacts). Commonly, the plans have a section dedicated to strategies as described above. The team specifically looked at the mitigation strategies section and assigned a value of one (1) to plans in which the specific GHG emissions reduction strategy was present in the relevant section.

Since the regional agencies and municipalities develop other planning documents, the team noted and discussed the following regarding a particular strategy:

- The CAP references the municipality's General Plan (GP) regarding a particular strategy.
- A strategy is detailed in a document/plan other than SCS, CAP, or GP. These might include specific plans or transportation plans.
- The text describing the policy is considered for the future. For example, the strategy is included in the segments of the plan concerning future considerations, such as a forecast or a vision.
- An action detailed in the adaptation segment of the SCS/CAP.

The instances described above were assigned a zero (0) value in the dataset created for quantitative analysis. Yet, they were used in the content analysis as a guiding tool for identifying trends in climate action planning. They helped examine the possible links between plan adoption dates, plan versions, city locations and sizes, and similar properties, to better understand efforts to reduce GHG emissions.

2.3 Results and Discussion

The following section contains the content analysis findings. The GHG emissions reduction strategies were discussed in four categories: transportation, land use, Transportation Demand Management (TDM), and cross-cutting issues (e.g., collaborating with other governmental organizations). For each category, the authors note the prevalence of specific strategies in analyzed planning documents and discuss common patterns that illustrate the range of policy actions on the regional and local level, their (dis)similarities, and other important qualities.

Transportation Infrastructure / Built Environment

As Table 4 shows, the common transportation strategies in SCSs and CAPs include active transportation strategies, such as improving pedestrian infrastructure and access, bicycle infrastructure, and developing a network of complete streets. These strategies are present in all analyzed SCSs. Similarly, most of the analyzed CAPs include bicycle and pedestrian strategies (19/20 cities). The exception is Lodi. The strategy related to complete streets is present in ten CAPs. Four cities refer to their respective GPs for complete streets strategies. One city, Riverside, refers to a related planning document, specifically an Active Transportation Plan (ATP). Broadly speaking, pedestrian and bicycle infrastructure is part of the complete streets policy. Moreover, the State of California has been developing its complete streets policy for at least the last two decades, as evident from a series of four Caltrans Deputy Directives. The 2001 directive introduced the policy through “Accommodating Non-Motorized Travel,” and the latest directive, “Complete Streets” DP-37, enacted at the end of 2021, mandates all Caltrans-funded projects implement the complete streets policy by accommodating a comfortable environment for all transit modes.¹⁰ In parallel to this policy development, different levels of government enacted a range of programs, plans, and actions that relate to active transportation and are often overlapping with complete streets policy, depending on the types of plans the jurisdiction has developed over time. More importantly, most analyzed plans include active transportation strategies, which are well supported through the State legislative, funding, and technical assistance programs.

Table 4. Regional and Local Transportation Strategies

| City | MPO | Plan date | Transportation Infrastructure / Built Environment | | | | | | | | | | |
|----------------------|------------|-----------|---|------------|------------------|--------------|------------------|--------------|--------------------------------|-----------------|---------------------------------|----------------|----------------|
| | | | Bicycle | Pedestrian | Complete Streets | Mass Transit | Electric Vehicle | Ride-sharing | Low-carbon / Alt. fuel Vehicle | Autonomous Veh. | Climate-friendly infrastructure | Vehicle Idling | Goods Movement |
| San Diego | SANDAG | 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ |
| | | 2015 | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | | ✓ | |
| | Oceanside | 2019 | ✓ | ✓ | ✓ | | ✓ | | ✓ | | ✓ | | |
| | Escondido | 2021 | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | | ✓ | |
| El Cajon | | 2019 | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | |
| Stockton | SJCOG | 2018 | ✓ | ✓ | ✓ | ✓ | | | | | | | ✓ |
| | | 2014 | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | | ✓ | ✓ |
| | Manteca | 2013 | ✓ | ✓ | ✓ | | ✓ | | ✓ | | | | |
| | Lodi | 2014 | | | | ✓ | | ✓ | | ✓ | | | |
| | Tracy | 2011 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | ✓ |
| San Francisco | MTC/ABAG | 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| | | 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | ✓ |
| | San Jose | 2018 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ |
| | Oakland | 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | ✓ |
| | Fremont | 2012 | ✓ | ✓ | | | ✓ | ✓ | ✓ | | | ✓ | |
| Los Angeles | SCAG | 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ |
| | | 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ |
| | Santa Ana | 2015 | ✓ | ✓ | | ✓ | | | ✓ | | ✓ | ✓ | |
| | Long Beach | 2021 | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | ✓ | | ✓ |
| Riverside | | 2016 | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | |
| Roseville | SACOG | 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | | | |
| | | 2010 | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | |
| | Elk Grove | 2019 | ✓ | ✓ | | | ✓ | ✓ | | | | | ✓ |
| | Yuba City | 2016 | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | | ✓ | | |
| | Sacramento | 2012 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | | ✓ |
| # of policies (MPO) | | | 5 | 5 | 5 | 5 | 4 | 4 | 3 | 2 | 1 | 2 | 3 |
| # of policies (city) | | | 19 | 19 | 12 | 16 | 18 | 15 | 18 | 2 | 14 | 7 | 10 |

Improving the efficiency of mass transit is another vital transportation strategy included in all regional plans. On a local level, this strategy was found in fifteen CAPs. One CAP refers to the

city's GP, and another city uses other planning documents to discuss mass transit strategies. Mass transit is briefly mentioned in two (Fremont and Manteca) CAPs and is not present in any form in one CAP.

Major hubs of urban activity—Los Angeles, San Francisco-Oakland, and San Jose—all plan to increase mass transit ridership by continually upgrading their systems to achieve more robust, efficient, and affordable transit networks that include various transit modes and operators, aim to cover the entire jurisdiction, and integrate into the region. These cities also desire to improve the transit experience by reducing travel time, facilitating efficient boarding, increasing safety and inclusiveness, and solving local issues, such as reducing heat exposure through cooling infrastructure in LA.

On the other hand, the mid-size and smaller cities mostly frame their strategies in relation to the transit providers—often the regional transit agencies. Even though the larger cities also collaborate with the agencies that usually cover larger areas than the cities (e.g., Caltrain or VTA in the Silicon Valley), smaller towns' policies are mainly designed to supplement the regional operator efforts. These supplemental policies include incentives, promotions, subsidies, the adoption of design guidelines in areas close to transit stops and hubs, and the facilitation of technological services such as GPS tracking. These cities also work on researching the current coverage and aim to supplement the network with ride-share, shuttle, and micromobility options.

Strategies to increase the use of electric vehicles and low-carbon or other alternative fuels aim to lower the GHG emissions beyond the transportation mode choice. Electric vehicle (EV) strategies are addressed in all analyzed SCSs except the SJCOG's. The regional efforts mainly focus on financing, charging facilities, and electrification of transit, fleet, and goods movement. Most cities (18/20) have an EV strategy in their CAP and offer a comprehensive set of electric vehicle strategies, ranging from EV charging station networks to logistical and infrastructural preparation for larger-scale use of EVs. Many cities include EV charger requirements in new development requirements (Ready, Set, Charge, California!).

Three MPOs have strategies to increase the share of low-carbon or other alternative fuels. Additionally, SACOG mentioned them in the vision segment of their SCS, and SJCOG included it in a piece about technology. Eighteen out of twenty cities have non-carbon or other alternative fuels strategies. The cities that do not have such strategies are Elk Grove and Lodi. These strategies can be seen as cross-cutting strategies on a local level. They often overlap with electric vehicles, autonomous vehicles, energy conservation, etc., and pertain to the city's fleet, construction vehicles, mass transit, and goods movement.

The autonomous vehicle strategy is new to most analyzed plans and is considered the next step toward innovation, electrification, and automation. The two biggest and most populated MPOs, SCAG and MTC/ABAG, have an autonomous vehicles-related statement embedded in their core vision and forecasting and transportation data modeling. These authorities see the share of autonomous vehicles increasing in the future and becoming an essential part of transportation

infrastructure planning. In a similar fashion, but to a lesser extent, SJCOG and SACOG included sections about autonomous vehicles in their forecasts, expressing a desire to embrace AVs once the technology is more developed. Only SANDAG does not mention autonomous vehicles. San Jose and Los Angeles incorporated autonomous vehicles strategies into their CAPs as they want to position themselves as leaders in enabling and testing new technologies in transportation.

Agencies and jurisdictions diversify the TLU strategy set by including policy actions such as ridesharing and vehicle idling. Ridesharing is addressed in four out of five SCSs (all but SJCOG). Regionally, ridesharing primarily focuses on regional commute programs and highway lane management. Fifteen cities addressed ridesharing as a strategy in CAPs, while four other cities mentioned ridesharing in parts of their plans that do not address GHG strategies directly. One city, Oceanside, does not mention ridesharing at all. On a local level, the strategies range from various commute-related programs to city- and neighborhood-level infrastructure and are often combined with curb and parking management. SCAG and SANDAG (two out of five MPOs) have strategies that address vehicle idling, while SACOG discusses idling in the plan's forecast section. Vehicle idling is tied to technological innovation and transportation network efficiency in regional plans. SANDAG aspires to dynamically manage curb space to improve the overall transportation system, including lowering the time vehicles spend idling. SCAG's SCS addressed idling through goods movement by the "Truck Bottleneck Relief" strategy. About a third (7/20) cities have vehicle idling strategies, which aim to reduce GHG emissions from vehicle idling through transportation system innovation and improvements. A simple example includes traffic signal synchronization and roundabouts, while more complex proposals aim to develop intelligent transportation systems (ITS). Vehicle idling is sometimes addressed with goods movement at the local level since idling trucks produce a significant amount of GHGs. On the other hand, Fremont, for example, has a set of locally focused strategies that should reduce idling around schools, childcare facilities, and drive-throughs.

Increasing the share of climate-friendly infrastructure, sometimes referred to as "green infrastructure," in the transportation network helps reduce GHG emissions through carbon capture. At the same time, climate-friendly infrastructure is often considered a more desirable form of active transportation infrastructure as it provides an aesthetically pleasing and comfortable walking and biking environment. MTC/ABAG is the only MPO that includes climate-friendly infrastructure in the SCS. SANDAG mentions climate-friendly infrastructure, but the other three MPOs do not include this strategy. Climate-friendly infrastructure is more thoroughly addressed on a local level. Fourteen of twenty analyzed cities do include this strategy. For example, San Diego, Fremont, and Escondido included green infrastructure through the adaptation strategies, whereas Manteca and Lodi only mentioned it. Most cities focus on lowering energy expenditure by installing solar panels and energy-efficient lighting on streets and parking lots, an approach usually found in the energy conservation segment. Climate-friendly infrastructure strategies sometimes overlap with climate adaptation strategies, especially in urban heat and stormwater management, with techniques such as reflective and cooling pavement, porous pavement, and planting shade vegetation.

A significant amount of GHG emissions comes from goods movement, and strategies to reduce them are common in analyzed plans. Goods movement strategies were addressed in three out of five SCSs. MTC/ABAG, the agency that did not develop a goods movement strategy, references a regional goods movement study. SACOG, on the other hand, does not have a strategy in the current SCS iteration, but had a detailed analysis in the previous version. SJCOG emphasizes the economic aspect of the goods movement since this industry is the most vital sector in the region. On the other hand, SCAG and SANDAG focus on reducing GHG from freight by advancing infrastructure and employing new technologies in all networks that contribute to goods movement, from air cargo, through railroads and roadways, to maritime systems. Notably, the final step in goods delivery, when the product is handed to a customer, referred to as the last mile delivery, is also addressed. A similar approach is carried out at the city level to optimize and improve the infrastructure and base goods movement energy use on electric energy. Half of the analyzed cities have relevant goods movement strategies in their CAPs.

Land-use Policies

The prevalence of regional and local land use strategies geared towards lowering GHG emissions are depicted in Table 5. Common land use strategies, including transit-oriented development (TOD), infill development, housing near development centers, and housing affordability and jobs-housing balance, are consistently found throughout the analyzed plans. They are developed by all regional agencies and presented in the SCSs we analyzed. TOD strategy is adopted in seventeen of twenty cities, infill development strategy in sixteen of twenty cities, housing near development centers in fourteen cities, and housing affordability and jobs-housing balance in twelve cities. Therefore, it is safe to assume that implementing these strategies is vertically integrated, meaning that it “flows down” from the state to the municipal level, although some variations are present.

Table 5. Regional and Local Land-use Strategies

| City | MPO | Plan date | Land-Use Policies | | | | | | | | | |
|----------------------|--------|-----------|-------------------|--------|--------------|-------------------------------|-------------------------------|---------------------|-----|----------------------|--------------|---------------|
| | | | TOD | Infill | ADU Programs | Housing Near Activity Centers | Affordab. / Jobs-Housing Bal. | Preserve Open Space | UGB | Parking Requirements | Urban Forest | Port Policies |
| | SANDAG | 2021 | ✓ | ✓ | | ✓ | ✓ | ✓ | | | | ✓ |
| San Diego | | 2015 | ✓ | ✓ | | | | ✓ | | ✓ | | |
| Oceanside | | 2019 | ✓ | ✓ | | | | ✓ | | | ✓ | |
| Escondido | | 2021 | ✓ | ✓ | | | | ✓ | | ✓ | ✓ | |
| El Cajon | | 2019 | ✓ | ✓ | | ✓ | | | | ✓ | ✓ | |
| | SJCOG | 2018 | ✓ | ✓ | | ✓ | ✓ | ✓ | | | | |
| Stockton | | 2014 | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | |
| Manteca | | 2013 | ✓ | ✓ | | ✓ | | | | ✓ | ✓ | |
| Lodi | | 2014 | | | | | | | | ✓ | ✓ | |
| Tracy | | 2011 | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | |
| | MTC | 2021 | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ | ✓ | | |
| San Francisco | | 2021 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ |
| San Jose | | 2018 | ✓ | ✓ | | ✓ | ✓ | | | | | |
| Oakland | | 2020 | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ |
| Fremont | | 2012 | ✓ | ✓ | | ✓ | | | | ✓ | | |
| | SCAG | 2020 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | |
| Los Angeles | | 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ |
| Santa Ana | | 2015 | | | | ✓ | ✓ | | | ✓ | | |
| Long Beach | | 2021 | ✓ | ✓ | | ✓ | ✓ | | | ✓ | ✓ | ✓ |
| Riverside | | 2016 | ✓ | ✓ | | ✓ | ✓ | | | ✓ | ✓ | |
| | SACOG | 2019 | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | | | | |
| Roseville | | 2010 | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | |
| Elk Grove | | 2019 | ✓ | | | | ✓ | | | | ✓ | |
| Yuba City | | 2016 | | | | | | | | | ✓ | |
| Sacramento | | 2012 | ✓ | ✓ | | ✓ | ✓ | ✓ | | ✓ | ✓ | |
| # of policies (MPO) | | | 5 | 5 | 2 | 5 | 5 | 5 | 1 | 2 | 1 | 1 |
| # of policies (city) | | | 17 | 16 | 2 | 14 | 12 | 10 | 0 | 16 | 16 | 4 |

Nevertheless, cities approach housing development near activity centers differently. Fremont aims to develop housing within walking distance of “basic services,” Oakland plans to place housing near “essential destinations of everyday life,” and Sacramento proactively plans “residential

neighborhood centers.” While all three jurisdictions aim to connect housing with activity centers, the definitions of and approaches to planning the activity centers differ. “Basic services” and “essential destinations of everyday life” are communicated similarly and imply a process of identifying existing activity centers. In contrast, Sacramento’s approach suggests the creation of new activity centers. Ultimately, all three cities want shorter distances between housing and services, which could lead to fewer vehicle trips. Several smaller cities (Roseville, El Cajon, Long Beach, Riverside, Stockton, Tracy) include a combination of mixed-use, infill, and TOD strategies in their CAPs. San Diego has housing development near activity centers detailed in their GP, as the “City of Villages” policy. Since housing development near activity centers strategy is incorporated in all the SCSs we analyzed, some cities utilize the MPO’s planning efforts and methodology or the data in local planning. One example of such regional collaboration is the “Smart Growth Policy” in Oceanside’s CAP, which relies on SANDAG’s assessment and catalog of the smart growth opportunity areas (SGOAs). The strategies that link housing affordability and jobs-housing balance vary mainly based on the city’s size. The mid-size and smaller cities such as Fremont and Escondido tend to address this issue as part of their economic development strategy. Bigger cities such as San José, Oakland, and San Francisco consider commuting patterns, overall housing affordability, and equity when planning to house local workers affordably.

Another strategy addressed by all five MPOs and by half of the analyzed cities is preserving open space, farmland, natural beauty, and critical environmental areas. Some cities, such as Sacramento, see preservation and conservation as part of sustainable growth patterns and project design, while others often overlap it with climate adaptation efforts. Similarly, open space, natural beauty, and critical environmental areas preservation (i.e., preserve open space) strategies differ between larger and smaller jurisdictions as they are influenced by circumstances, including the presence of agricultural activity, local geography, and the overall level of urbanization altering the natural environment. For example, San Francisco and Los Angeles introduce “healthy ecosystems” that treat urban and natural environments as one and aim to achieve a balance with no compromise to environmental health. In Oakland, the emphasis on equity is also apparent in this policy area.

Parking, as a theme, is emerging as a common land use strategy in climate action planning. Parking requirements are part of the two most significant region’s SCSs, SCAG, and MTC/ABAG, while parking-related strategies are present in sixteen of twenty analyzed CAPs. Regions work on legislation and planning efforts to reform the parking requirements in a broader effort to provide more effective strategies in housing policy. MTC/ABAG, on the other hand, also introduced parking fees to confront solo driving. On the municipal level, the overarching theme is similar to the regional, and in most cases, geared toward “unbundled parking” (where parking space is rented or purchased separately from residential units) and decreasing or eliminating the parking minimums. Cities are also interested in curb space innovation, shared parking strategies, and coupling energy conservation efforts with parking efficiency through preferential parking for EVs and solar panel installation on parking lots.

Urban forest and urban growth boundary (UGB) are strategies that reduce GHGs but are better implemented on a local than a regional level. For example, SCAG is the only regional agency that developed an urban forest strategy and defined it as a “multi-benefit land-use strategy.” The multiple benefits of an urban forest, as described in Connect SoCal, may include enhanced active transportation infrastructure, traffic calming, street surface cooling, trail connectivity, etc. Urban forests, in contrast, are included in 16 municipal plans as most cities want to increase the number of trees planted and have established, or plan to establish city nurseries and tree planting foundations. UGB is an even less common GHG reduction strategy than urban forests in analyzed plans. Of all the plans analyzed, both regional and municipal, only MTC/ABAG has this strategy, and the city of San José refers to their GP, where the UGB is detailed.

Ports are part of goods movement infrastructure and profoundly impact GHG emissions. Since many port authorities developed their own CAPs, there is limited emphasis on ports in regional and local climate action planning. Only SANDAG includes port policies in their SCS, coupled with goods movement strategies. The focus here is on using electric trucks in port operations. In analyzed CAPs, Oakland and Long Beach have a similar approach to SANDAG’s, relying on drayage truck electrification or hydrogen fuel use. San Francisco’s and San Diego’s Ports are separate planning agencies that have developed CAPs. In contrast, Los Angeles’s CAP specifically targets the ship’s fuel and drayage truck (port to the first destination) emissions.

Transportation Demand Management (TDM) Strategies

The regional and local TDM policy actions, widely used and well-known strategies to reduce GHG emissions, are displayed in Table 6.

Table 6. Regional and Local TDM Strategies

| City | MPO | Plan date | TDM | | |
|----------------------|----------|-----------|-----|--|------------------------|
| | | | TDM | Other Programs or Incentives to Lessen Driving | Education and Outreach |
| | SANDAG | 2021 | ✓ | | ✓ |
| San Diego | | 2015 | | | |
| Oceanside | | 2019 | ✓ | | |
| Escondido | | 2021 | ✓ | | ✓ |
| El Cajon | | 2019 | ✓ | | ✓ |
| | SJCOG | 2018 | ✓ | | |
| Stockton | | 2014 | ✓ | | ✓ |
| Manteca | | 2013 | ✓ | ✓ | |
| Lodi | | 2014 | ✓ | | ✓ |
| Tracy | | 2011 | ✓ | | ✓ |
| | MTC/ABAG | 2021 | ✓ | | |
| San Francisco | | 2021 | ✓ | | ✓ |
| San Jose | | 2018 | | | |
| Oakland | | 2020 | ✓ | ✓ | ✓ |
| Fremont | | 2012 | ✓ | ✓ | |
| | SCAG | 2020 | ✓ | ✓ | |
| Los Angeles | | 2019 | ✓ | | ✓ |
| Santa Ana | | 2015 | | | |
| Long Beach | | 2021 | ✓ | ✓ | |
| Riverside | | 2016 | ✓ | | |
| | SACOG | 2019 | ✓ | ✓ | ✓ |
| Roseville | | 2010 | ✓ | ✓ | ✓ |
| Elk Grove | | 2019 | ✓ | | ✓ |
| Yuba City | | 2016 | ✓ | | ✓ |
| Sacramento | | 2012 | ✓ | | ✓ |
| # of policies (MPO) | | | 5 | 2 | 2 |
| # of policies (city) | | | 18 | 5 | 12 |

All MPOs and almost all cities (18/20) have TDM strategies. Some MPOs and cities have transportation system improvement policies in their forecast. They envision technological improvements in monitoring and managing the traffic flow and the infrastructure in real-time, including all travel modes. Since TDM aims to address how efficiently commuters travel from and to work, these improvements would work synergistically with TDM actions. Another strategy

worth mentioning is an increase in telecommuting, as, for example, in Lodi. Lodi's CAP introduces "flextime," a strategy that encourages employers to implement telecommuting and alternative work schedules, where the latter allows employees to set an alternative work schedule, often resulting in a condensed four-day work week. The purpose of the flextime strategy is to reduce congestion and vehicle trips.

Education and outreach strategies to encourage people to choose alternatives to driving alone are widespread, ranging from bike and walk encouragement programs, alternative transportation pilot programs, and collaborative partnerships. Twelve of the twenty analyzed cities have some type of a strategy to educate their communities about sustainable practices, especially in transportation. Medium- to smaller-sized regions, such as SACOG and SANDAG, have education and outreach strategies to reduce GHG emissions, accounting for two out of five regions. SANDAG, one of the two regional agencies with an education and outreach strategy, calls for expanding the policy spectrum "beyond traditional TDM strategies and include shared streets, shared mobility pilots, micromobility incentives, technology-based solutions, and more."¹¹

Cross-cutting Issues

This section discusses cross-cutting issues in climate action planning, ranging from regional collaboration to addressing equity on the regional and local levels. The prevalence of policy actions is displayed in Table 7.

Table 7. Regional and Local Cross-cutting Issues

| City | MPO | Plan date | Cross-cutting Issues | | | |
|----------------------|-----------------|-----------|------------------------|-------|--|--------|
| | | | Regional Collaboration | Other | Community Involvement and Outreach (CIO) | Equity |
| | SANDAG | 2021 | ✓ | | ✓ | ✓ |
| San Diego | | 2015 | ✓ | | ✓ | |
| Oceanside | | 2019 | ✓ | | ✓ | |
| Escondido | | 2021 | ✓ | | | |
| El Cajon | | 2019 | ✓ | | ✓ | |
| | SJCOG | 2018 | ✓ | | ✓ | ✓ |
| Stockton | | 2014 | ✓ | | ✓ | |
| Manteca | | 2013 | ✓ | | ✓ | |
| Lodi | | 2014 | ✓ | | ✓ | |
| Tracy | | 2011 | ✓ | | ✓ | ✓ |
| | MTC/ABAG | 2021 | ✓ | | | ✓ |
| San Francisco | | 2021 | ✓ | ✓ | ✓ | ✓ |
| San Jose | | 2018 | | | | |
| Oakland | | 2020 | | | ✓ | ✓ |
| Fremont | | 2012 | ✓ | | | |
| | SCAG | 2020 | ✓ | | ✓ | ✓ |
| Los Angeles | | 2019 | ✓ | ✓ | ✓ | ✓ |
| Santa Ana | | 2015 | ✓ | | ✓ | |
| Long Beach | | 2021 | ✓ | ✓ | ✓ | ✓ |
| Riverside | | 2016 | ✓ | | ✓ | ✓ |
| | SACOG | 2019 | ✓ | | ✓ | ✓ |
| Roseville | | 2010 | ✓ | | ✓ | |
| Elk Grove | | 2019 | ✓ | | | |
| Yuba City | | 2016 | ✓ | | | |
| Sacramento | | 2012 | ✓ | | ✓ | ✓ |
| # of policies (MPO) | | | 5 | 0 | 4 | 5 |
| # of policies (city) | | | 18 | 3 | 15 | 7 |

Regional agencies are frequently the force fueling municipal efforts in climate action planning. All regional agencies have strategies that include collaboration and coordination with municipalities and state entities. SANDAG, a one-county regional agency, is exemplary for its efforts to develop a framework for local climate action planning. SANDAG has offered climate action planning services to member jurisdictions since 2016. These services include GHG emissions inventory and

no-cost planning staff assistance to local governments to update or develop CAPs. As a result of these efforts, nineteen out of twenty SANDAG member agencies developed a CAP. Additionally, SANDAG has published the Regional Framework for Climate Action Planning (ReCAP). ReCAP contains best practices for preparing local CAPs and monitoring the implementation.¹² The analyzed cities follow the lead, as eighteen of twenty local plans have regional collaboration strategies.

Similarly, community involvement and outreach strategies are omnipresent in analyzed plans. Engaging the community through community involvement and outreach (CIO) is present in four SCSs. MTC/ABAG does not include CIO as a strategy in the plan but has it as a separate plan. In fact, the Fixing America's Surface Transportation (FAST) Act, signed into law in 2015, requires regional planning agencies to engage all actors and stakeholders in their jurisdictions in public participation and coordinate with member jurisdictions and agencies. Consequently, all five regional agencies have developed a plan, commonly referred to as a Public Participation Plan (PPP) or Public Involvement Plan (PIP). CIO, as an essential aspect of planning, thus evolves with plan iterations. For example, SANDAG and MTC/ABAG put a considerable emphasis on tribal participation. Another example is enhanced online participation, which is often enriched with more on-site participation events in disadvantaged communities, mitigating the digital divide. Fifteen of twenty cities have the strategy in their CAPs. In addition to engaging the community in the planning process, local governments extend their CIO efforts to partner with the community actors in various GHG reduction activities, programs, or campaigns.

In an effort to develop a resilient and connected urban environment, a relatively new theme has emerged in climate action and regional planning: planning for equity. MPOs lead key equity efforts at the regional scale, since all include equity in their SCSs. Seven of twenty cities have strategies to increase equity. Except for Tracy, all are more prominent cities. One of the best examples of incorporating equity in climate action planning comes from the city of Oakland. Its Equitable CAP, or ECAP, introduces the term "frontline communities" to refer to groups that face intersecting vulnerabilities including racial, environmental, and socioeconomic impacts. Oakland's ECAP strategies include an equity perspective, and the plan calls for tracing ECAP actions to all other local planning documents.

3. Alignment Operationalization

The goal of this chapter is twofold: (1) using the data gathered through content analysis of local CAPs and regional SCSs to measure the level of alignment between their Transportation and Land Use (TLU) strategies (i.e., operationalizing an alignment score); and (2) examining the relationship between the alignment of these strategies, local level actions, and vehicle trip reduction over time. The chapter is organized into two sections: first, the “Methods” section, in which the authors explain the sample and the data and variables used to operationalize the alignment score, and second, the “Results and Discussion” section, in which the authors discuss the determinants of vehicle trip reduction and the impact of policy alignment through a sample model as well as the estimated alignment scores for five TLU categories: (1) Transportation infrastructure (built environment) alignment, (2) Land use policies alignment, (3) Transportation demand management policies alignment, (4) Cross-cutting issues policies alignment, and (5) Overall alignment. Ultimately, the alignment scores were implemented in a web map visualization for the cities in the study sample to provide public access to our major findings.

3.1 Methods

Sample

The first step for operationalization of the alignment score is to quantify the vehicle trip reduction impact of MPO-City alignment for each of the four particular TLU strategy categories plus overall alignment (i.e., (1) Transportation infrastructure (built environment) alignment, (2) Land use policies alignment, (3) Transportation demand management policies alignment, (4) Cross-cutting issues policies alignment) for which we collected data through content analysis of CAPs and SCSs (please review chapter two for details) in tandem with (5) overall alignment. Then the quantified vehicle trip reduction impacts were used as the weights for each policy in the four categories to compute the alignment score. The baseline for alignment score is a dummy variable, which is “1” when both the city and MPO have the policy in their plans; otherwise, it is “0” (i.e., one or both do not have the strategy). We then used this dummy variable to compute the ultimate MPO-City impact on vehicle trip reduction through a series of statistical models and used the estimated impact for computing alignment scores.

In order to quantify this impact, the authors used a series of linear regression models at the block group level for the selected 20 cities, which we discuss in full detail in the methods section. The linear regression models have a sample of 6,513 census block groups in the 25 cities for which we conducted the content analysis. The sample size of 6,513 block groups is a sample size after model modifications. Census block groups (BGs) are statistical divisions of census tracts that contain between 600 and 3,000 people and are used to present data and control block numbering.¹³ The BG unit was selected for this model, because it is the most granular unit for which data is available. This helped increase the number of observations, and hence the statistical power of the final model.

Data and Variables

Table 8 provides full details for the variables used in the models, as well as their data sources. To collect the data for these variables, the list of cities compiled from the content analysis was used to obtain their boundaries in a GIS shapefile format from the Census Designated Places (2019)—the major data repository for shapefiles acquired from the U.S. Census website. Using city boundaries, the block groups were allotted to the cities if the block groups' population centroids¹⁴ were within a city's boundary.

Table 8. Variable Descriptions and Data Sources

| Variable | Description | Source | Mean (s.d.***) |
|--|--|-------------------------|------------------|
| Outcome variable | | | |
| 10-Yr nonauto c | 2010–2019 % change in non-auto work commuters | ACS* 5-Year Estimate | 0.17 (11.16) |
| Built environmental input variables | | | |
| Act Den | Gross activity density (employment + housing units) on unprotected land | SLD** estimated in 2018 | 32.44 (43.53) |
| Emp Ent | 5-tier employment entropy | SLD** estimated in 2018 | 0.61 (0.25) |
| Rd Den | Total road network density | SLD** estimated in 2018 | 26.34 (8.92) |
| TransitFq_CP | Aggregate frequency of transit service per capita | SLD** estimated in 2018 | 0.01 (0.09) |
| Sociodemographic input variables | | | |
| Pop | Total population 2019 | ACS* 5-Year Estimate | 1674.48 (991.23) |
| Emp_% | % of employed working age population | ACS* 5-Year Estimate | 94.09 (4.92) |
| Edu_% | % of 25yr old and above with bachelor or higher degrees, 2019 | ACS* 5-Year Estimate | 37.05 (23.75) |
| NearWork_% | % of working age population living within a 30-minute commute to work 2019 | ACS* 5-Year Estimate | 52.18 (15.61) |
| Mid-age_% | Percentage of 45–64-year-old residents in 2019 | ACS* 5-Year Estimate | 24.82 (15.61) |
| Non-auto_10_% | % of non-auto work commuters in 2010 | ACS* 5-Year Estimate | 0.16 (0.18) |
| Policy input variable (major variable of interest) | | | |
| Alignment | 1 if both the city's and MPO's plans have the policy otherwise 0 | Content analysis | N/A |

* American Community Survey

** Smart Location Database

*** Standard deviation

The analysis consists of three major categories of variables. The first category includes built environment attributes that are widely accepted as the strong determinants of vehicle commute patterns in the communities. Therefore, the statistical model must control for these factors. The data for measuring these factors were assembled from the Environmental Protection Agency's (EPA's) Smart Location Database (SLD). The SLD summarizes more than 90 different indicators associated with the built environment and location efficiency including density of development, diversity of land use, street network design, and accessibility to destinations as well as various demographic and employment statistics which are mostly available for all BGs.¹⁵ The

models utilized in this research control for the four major built environment variables (i.e., “the 4 Ds”):¹⁶ activity density (i.e., population plus employment per square mile land area), land-use diversity (i.e., entropy or degree of job mixing), street design (i.e., intersection density), and distance to transit (for which we used frequency of transit service as a strong proxy for this D).

The statistical model also controls for another category of factors that strongly impact commute patterns: the demographic attributes of each block group. This set of variables includes the size of a block group (i.e., total population), percentage of employed working-age residents, education status (i.e., percentage of residents 25 years of age and older who have Bachelor’s or higher degrees), and age (share of middle–adulthood-aged residents). Furthermore, the other two major variables that can potentially play a key role in work commute patterns are the place of work and the residents’ auto-dependency. To measure these two factors, the authors used percentages of commuters who live within a 30-minute distance to work and the percentage of non-auto commuters in 2010.

Analytical Method

The methods involved estimating weights for the MPO-City alignment for each of the GHG emissions reduction TLU strategies. These weights need to reflect the impact of each alignment on GHG emissions reduction, which has been proxied using the ten-year vehicle commute reduction. Using the t-values estimated in the model, the team was able to quantify the vehicle trip reduction impact of the MPO-City alignment for each of the TLU strategies as the weight for computing the final score. T-values/t-statistics measure the statistical significance of an independent variable (i.e., in this case, the alignment variable) in explaining the dependent variable (ten-year vehicle commute reduction).¹⁷ Ultimately, we estimated 24 regression models for 24 TLU strategies. Three policies of urban growth boundary (ugboundalig), port policies (portalig), and other regional policies (regotheralig) do not affect vehicle trips; therefore, the authors did not include them in the models.

In the linear regression models, the research team accounted for the four main assumptions of Ordinary Least Squares (OLS) regression including linearity, normality, multicollinearity, and homoscedasticity. The linearity was tested using scatter plot chart mix, which did not suggest the need to transform the variables. For multicollinearity, the team used the Variance Inflation Factor (VIF) value of 2.5 as a threshold to eliminate the risk of multicollinearity. This threshold is appropriate because it is widely accepted that VIF values above 2.5 could be problematic.¹⁸ The maximum VIF among all of our models is 1.67, and the average VIF of all models is 1.2 (please see appendices for the results of all regression models). For normality, we used the skewness measures obtained from Stata, showing the degree and direction of skewness. The value of 0 indicates a symmetric distribution (normal distribution), while negative and positive values indicate that the distribution is skewed to the left or right, respectively. The skewness measure for our outcome variable is 0.12, indicating a near normal distribution. Finally, we controlled for the assumption of homoscedasticity by using the robust standard error estimates. According to

White,¹⁹ robust standard errors relax the homoscedasticity assumption by adjusting the test statistics and p-values with respect to the level of heteroscedasticity of the error term.

Finally, the t-values estimated in these 24 models were stored as the weights for the dummy variable that indicate whether there is an alignment for each TLU strategy between the city's plan and the MPO's SCS. Once the alignment scores were estimated, they were normalized to a value that ranges between 0 and 100. Variable normalization is usually used when multiple variables are measured on different scales; the goal is to have each of the variables on the same range. Using a Min-Max Normalization¹ method in this case, the goal is to convert each data value to a value between 0 and 100. Therefore, the minimum value will be 0 and the maximum value will be 100 after normalization. Hence, it is important to note that the value 0 in the normalized variable is not 0 per se, it is just the minimum value converted to 0; however, the minimum value may or may not be 0.²⁰ In the next section, the team presents a sample of the regression models and the alignment scores in four major categories.

¹ Formula: New value = (value – min) / (max – min) * 100.

4. Results and Discussion

The 24 regression models were estimated using Stata 15.1. While the results of all regression models are included in the appendices, the authors reviewed the results of a sample model for the MPO-City alignment in supporting climate-friendly infrastructure. This sample model has results that are quite similar to the other models in terms of both coefficients and model robustness (please see the expanded results in the appendices). The coefficients of all variables in this sample model have the expected signs, and most of them are significant at the 0.05 level or beyond. R2 indicates fitness of models with relatively high values: 0.26. This indicates that the sample model explains more than 26% of the variation of the ten-year vehicle trip reduction. The R2 for other models are also close to 20% and are explained in the appendices. In what follows, we discuss our model results (i.e., determinants of vehicle trip reduction) as well as the use of the model for computing the alignment scores and assessing cities alignment status.

The Impact of the Alignment on Ten-Year Vehicle Trip Reduction

In the first section we review the observed values in our sample regression model, which measures the determinants of ten-year vehicle trip reduction. Table 9 reports the results of our sample regression model, which are quite similar to findings in other 23 models (as reported in the Appendix).

Table 9. Results of a Sample Regression Model for Estimating Weights for the Alignment Scores

| nonautopct_cgeN19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] |
|-------------------|-------------|------------------|--------|-------|-----------------------|
| CF_alig | 7.188128 | 0.4224629 | 17.01 | 0 | 6.359918 8.016338 |
| Non-auto_10_% | -34.94133 | 1.987726 | -17.58 | 0 | -38.83813 -31.04453 |
| NearWork_% | -0.0709271 | 0.0104521 | -6.79 | 0 | -0.0914178 -0.0504364 |
| Pop | -0.0003308 | 0.0901657 | -2 | 0.046 | -0.0006557 -5.84E-06 |
| Mid-adu-age_% | -0.2064419 | 0.0269949 | -7.65 | 0 | -0.2593636 -0.1535201 |
| Emp_% | -0.1639812 | 0.0374421 | -4.38 | 0 | -0.237384 -0.0905784 |
| Edu_% | 0.1086292 | 0.0071005 | 15.3 | 0 | 0.0947092 0.1225492 |
| Act den | 0.0517949 | 0.0142766 | 3.63 | 0 | 0.0238065 0.0797832 |
| Emp ent | 1.243296 | 0.6127758 | 2.03 | 0.043 | 0.0419904 2.444601 |
| Rd Den | 0.0947417 | 0.0203568 | 4.65 | 0 | 0.0548336 0.1346499 |
| TransFq_CP | 38.64732 | 16.57827 | 2.33 | 0.02 | 6.146737 71.1479 |
| cons | 19.90315 | 3.593436 | 5.54 | 0 | 12.85846 26.94784 |

Number of obs: 5,080; F(11, 5068) = 98.11; Prob > F = 0.000; R-Squared = 0.2618; Root MSE = 10.069

According to the constant value recorded in our model, we expect an average of almost a 20% increase in non-auto commute among all block groups in our sample that can be attributed to climate planning strategies. Among all the variables in our model, the top two with the strongest positive correlation with the increase in non-auto commute trips are the alignment between cities and MPOs in addressing the strategies for climate-friendly infrastructure and a share of the educated residents with university degrees. Accordingly, on average, a city's block group has more than a 7% increase in non-auto commute if the city and its MPOs are aligned in terms of having strategies to support climate-friendly infrastructure. Climate-friendly infrastructure strategies often focus on reducing the GHG emissions impact of the transportation infrastructure through reducing energy use or carbon capture, but several common strategies in this category produce a significant co-benefit: greater walkability. For example, one common strategy in this category includes planting trees and/or preserving tree canopy cover, which the literature links to greater walkability.²¹

Turning to the negative factors found in the model, population size was one of the major indicators of an increase in vehicle trips. In other words, the highly populated block groups that already had an active commute pattern in 2010 are at strong odds for increasing the active/non-auto working commute pattern further between 2010 and 2019. This is not completely unexpected because it is often more difficult to further increase active transportation if many residents were already utilizing active transportation modes. Active transportation options are not for everyone, and some individuals will rely on other modes of transportation regardless of local or regional policies to encourage active transportation. Furthermore, the stronger presence of middle-aged residents also indicates less active commuting to work. One explanation for this is that middle-aged adults are more likely to have complex family responsibilities or physical challenges, making the use of active transportation options more difficult. It is possible that young and active commuters in 2010 started relying on vehicles to meet their transportation needs as they aged. Furthermore, the model also shows that the economic status of a block group could be at odds with vehicle trip reduction. Another study on vehicle trip reduction, specifically on off-site VMT mitigation, confirms that sprawled, higher-income places tend to have a higher driving rate because of their discretionary income.²² This role is particularly strong if residents are living within a 30-minute driving distance of their place of work. Coupling this finding with the supportive impact found for transit, this finding also raises questions about the effectiveness of job-housing balance policies without adequate transit systems in place.

These regression models also allowed the research team to assess the difference in the impacts of local-level policies versus local and regional alignment of climate policies. To conduct this assessment, the research team ran the second series of 24 regression models using a dummy variable which indicates whether the city of a block group has the policy (dummy: 1) or not (otherwise: 0). The t-values were recorded for both models and reported in Tables 10 to 13 below to allow the comparison.

Tables 10 to 13 report the t-values estimated through the regression models, which quantified the impacts of MPO-City alignment and local level policy alone on the ten-year vehicle trip reduction. In the interpretation of these below tables, it is important to note that for some policies (e.g., TOD), comparison between the impact of MPO-City alignment and the impact of local policy independent of MPO is not possible. This is because for some policies, all the MPOs have a relevant strategy, while cities vary in terms of including these policies. In these cases, the dummy variable for MPO-City alignment and the city’s policy will be the same, and the model results are similar. These variables are distinguished by an asterisk in the results tables.

Transportation Infrastructure / Built Environment

As the values in Tables 10–13 show, alignment for all policies does not have a significant positive impact on vehicle trip reduction. For instance, for the first category of policies (i.e., Transportation infrastructure/Built Environment, Table 10), the most effective group of strategies is climate-friendly infrastructure. The purpose of climate-friendly infrastructure is to help mitigate GHG emissions and simultaneously provide resilience against climate impacts, such as flooding and heat waves. Climate-friendly infrastructure strategies have a wide range, from installing solar panels to preserving tree canopy cover. With much focus on planting trees and enhancing green spaces, climate-friendly infrastructure can also provide an aesthetically pleasing and comfortable walking and biking environment. When compared, the t-values of MPO-City alignment and local level policy, the alignment significantly increased the impact of the policy on the ten-year vehicle trip reduction. Thus, it is important to invest in the MPO-City alignment for the climate-friendly infrastructure strategies.

Table 10. Alignment Scores for Transportation Strategies

| Transportation Infrastructure / Built Environment | | | | | | | | | | |
|---|----------|-------------|-------------------|---------------|------------------|--------------|---------------------|---------------------------------|----------------|----------------|
| Policy | Bicycle* | Pedestrian* | Complete Streets* | Mass Transit* | Electric Vehicle | Ride-sharing | Autonomous Vehicle* | Climate-friendly infrastructure | Vehicle Idling | Goods Movement |
| MPO-City Align | 0.43 | 0.43 | 2.23 | 2.02 | -0.66 | -0.82 | -16.72 | 17.01 | -0.26 | -14.37 |
| City | 0.43 | 0.43 | 2.23 | 2.02 | 0.56 | -0.22 | -16.72 | 0.81 | -0.34 | 0.93 |

* Comparison is not possible because the dummy variable for MPO-City alignment and the City’s policy are the same (all the MPOs have the strategy in question).

The model also shows that policies supporting active transportation modes have a positive impact on vehicle trip reduction, particularly policies supporting mass transit and complete streets. Complete streets strategies mostly include enhancing active transportation infrastructure such as pedestrian and bicycle infrastructure. Therefore, complete streets strategies aim for developing a

network of complete streets that serve all transportation modes. However, the other strategies in this category do not have a positive impact on vehicle trip reduction.

Within the first category of strategies, except for the climate-friendly infrastructure strategies (for which our models showed the stronger effectiveness of MPO-City alignment than local action alone), the model demonstrates different results for all other policies, which a comparison between alignment and local action alone shows was possible. Among all the strategies, a city's action (independent of alignment with its MPO) for goods movement and electric vehicles are significantly more effective.

Land-use Policies

Table 11 below reports the results of t-values for the second category of strategies (i.e., land use policies), which are also found to have varying impacts that call for applying different weights in estimation of alignment scores. Among all the strategies in this category, MPO-City alignment in having strategies for preserving open space, farmland, natural beauty, and critical environmental areas has the strongest impact. It is worth noting that open space, natural beauty, and critical environmental areas preservation approaches differ between larger and smaller jurisdictions. The formulation of these strategies is also influenced by other circumstances, including the presence of agricultural activity, local geography, and the overall level of urbanization altering the natural environment. For example, San Francisco and Los Angeles introduced “healthy ecosystems” that treat urban and natural environments as one and aim to achieve a balance with no compromise to environmental health. There is a clear explanation for why a consistent strategy to preserve open space, farmland, and natural green spaces at both local and regional levels can help reduce vehicle trips. Preservation of farmland and open and natural spaces is a key strategy to combat sprawl and reduce the need for vehicle trips.

In addition to open space preservation strategies, our models showed that alignment in parking requirement strategies is another influential factor in reducing vehicle trips between 2010 and 2019. Such strategies could include parking fees to confront solo driving, or on the municipal level, can gear toward “unbundled parking” and decreasing or eliminating the parking minimums. As these strategies can limit parking availability and increase parking costs, people are more likely to use other modes for their daily work commute patterns. The MPO-City alignment in strategies for housing, such as housing development near activity centers or job-housing balance, as well as infill development strategies, also have positive impacts on reducing vehicle trips. Yet, when compared with open space preservation and parking requirements strategies, the impact of such strategies is lower.

Table 11. Alignment Scores for Land-use Strategies

| Land-Use Policies | | | | | | | | |
|-------------------|------|---------|--------------|--------------------------------|---------------------------------|----------------------|----------------------|--------------|
| Policy | TOD* | Infill* | ADU Programs | Housing Near Activity Centers* | Affordable / Jobs-Housing Bal.* | Preserve Open Space* | Parking Requirements | Urban Forest |
| MPO-City Align | 0.32 | 1.33 | -13.66 | 0.98 | 0.77 | 7.06 | 5.15 | -14.35 |
| City | 0.32 | 1.33 | -0.73 | 0.98 | 0.77 | 7.06 | 7.26 | 7.17 |

* Comparison is not possible because the dummy variable for MPO-City alignment and the City's policy are the same (all the MPOs have the strategy in question).

The only variables in the second category for which the t-values could be compared are ADU programs, parking requirements, and urban forest strategies. For all three of these variables, our models confirmed that a city's independent action is more effective, and, in some cases, the results are reversed. One major example is urban forest, for which, while the alignment has significant negative impact on vehicle trip reduction, the t-value for the city's independent action is positive and highly significant. Another major shift occurs for ADU programs, for which the MPO-City alignment has a significant negative impact, while the city's independent action does not have a significant impact.

TDM Policies

In the third category of strategies (Transportation Demand Management), the alignment of local and regional policies is reported in Table 12 below. The alignment is only important in TDM strategies related to programs that increase transit, walking, bicycling, and ridesharing modes. These TDM strategies had a very strong positive impact on vehicle trip reduction when local and regional efforts were well-aligned. These TDM strategies focus on increasing the efficiency of the transportation system by encouraging people to use existing infrastructure for transit, walking, bicycling, and ridesharing. One explanation for this is that the success of these TDM programs depends on both regional and local efforts, and particularly how these efforts are harmonized to help people switch to alternative modes of transportation.

Table 12. Alignment Scores for TDM Strategies

| TDM Policy | TDM* | Other Programs or Incentives to Lessen Driving | Education and Outreach |
|----------------|------|--|------------------------|
| MPO-City Align | 7.22 | -2.01 | -0.57 |
| City | 7.22 | 5.58 | 6.93 |

* Comparison is not possible because the dummy variable for MPO-City alignment and the City's policy are the same (all the MPOs have the strategy in question).

For the remaining strategies in this category, local independent action was more effective than acting in line with the MPO. Specifically, MPO-City alignment for education and outreach policies and other programs to lessen driving (e.g., strategies to encourage people to telework) did not result in reduced vehicle trips. Instead, local action was more effective in reducing vehicle trips. These results indicate the possible advantage of local community engagement and outreach programs in changing behavior.

Cross-cutting Issues

Ultimately, our models did not show a strong positive impact for the MPO-City alignment in strategies that fall in the last category (i.e., cross cutting issues). However, the only strategy with an insignificant positive impact was related to equity. Equity is a newer focus of many climate action plans and often includes various strategies such as protecting the vulnerable or front-line communities against climate impacts, as well as establishing racial equity and/or ensuring access to transit and jobs for low-income communities. As expected, our models suggest that ensuring equitable access to transit and provision of housing near transit or employment centers is a key strategy for reducing vehicle trips. Again, while the models did find an effective alignment in this category, the city's independent action is highly significant in reducing vehicle trips, as reported in Table 13 below.

Table 13. Alignment Scores for Cross-cutting Strategies

| Cross-cutting Issues | | | |
|----------------------|-------------------------|-------|--|
| Policy | Regional Collaboration* | Other | Community Involvement and Outreach (CIO) |
| MPO-City Align | -2.25 | -15.8 | 0.79 |
| City | -2.25 | 6.99 | 0.79 |

*Comparison is not possible because the dummy variable for MPO-City alignment and the City's policy are the same (all the MPOs have the strategy in question).

In conclusion, among all the variables for which we could conduct a comparison between MPO-City alignment and City's independent action, the MPO-City alignment was only significant for climate-friendly infrastructure policies. On the other hand, for all other variables, we found the city's independent action to be more effective for strategies for which the alignment either did not have a significant positive impact or the impact of the city's independent action was stronger. Cities' independent action in strategies for goods movement, urban forest, education and outreach in tandem with other programs to lessen driving, and CIO are found to be significantly effective in reducing vehicle trips, while the MPO-City alignment for these strategies has a reversed impact. Furthermore, while our models show that the MPO-City alignment for parking requirements has a positive impact on vehicle trip reduction, the impact of local independent action for this strategy is found to be stronger.

As these t-values indicate, the alignments in different policies have varying impacts that our alignment scores control for. Therefore, we used the 24 regression models in order to define a weighting value to use for each strategy for estimation of our alignment scores. T-values/t-statistics measure the statistical significance of an independent variable (which in our case is the alignment variable) in explaining the dependent variable (vehicle trip reduction). We used the t-stats reported in our model for each alignment dummy variable to weigh for each city's alignment status (t-stats*city's alignment dummy variable is 1 if both the city and MPO have the strategy, 0 otherwise). The final value for each policy category is the 0–100 normalized sum of weighted alignment dummy variables. In the following section, we present these scores to assess cities' status.

Alignment Scores

Table 14 presents the estimated t-values in the regression models which were interpreted in the previous section (also presented in Tables 10–13) and in this section will only be used for defining weights for estimating the alignment scores regardless of the size and sign of the value.

Table 14. Weights (i.e., t-values) from Models for MPO-City Alignment Variables

| Policy | Weight | Policy | Weight | Policy | Weight | Policy | Weight |
|---|--------|---|--------|---|--------|--|--------|
| Bicycle | 0.43 | Transit-oriented Development | 0.32 | TDM | 7.22 | Regional collaboration | -2.25 |
| Pedestrian | 0.43 | Infill development | 1.33 | Other programs or incentives to lessen driving | -2.01 | Community involvement and outreach (CIO) | -15.8 |
| Complete Street | 2.23 | ADU development program | -13.66 | Education and outreach | -0.57 | Equity | 0.79 |
| Mass Transit | 2.02 | Housing development near activity centers | 0.98 | | | | |
| Electric Vehicle | -0.66 | Job-housing balances | 0.77 | | | | |
| Ride Sharing | -0.82 | Preserve Open-Space | 7.06 | | | | |
| Low Carbon Fuel | 0.791 | Parking requirements | 5.15 | | | | |
| Autonomous Vehicle | -16.72 | Urban forest | -14.35 | | | | |
| Climate-Friendly Infrastructure | 17.01 | | | | | | |
| Vehicle Idling | -0.26 | | | | | | |
| Goods Movement | -14.37 | | | | | | |
| Transportation infrastructure/Built Environment | | Land Use (LU) Policies | | Transportation Demand Management (TDM) Policies | | Cross cutting edges | |

Bold variables are significant with the critical t-value $|t| \geq 1.96$

Table 15 below presents the estimated alignment scores with the breakdown by policy categories in addition to the overall score (i.e., including all the policies and strategies). It is again important to note that Table 14 shows the weights used for estimating these scores before the 0–100 normalization. The four categories of policies included in our content analysis (for which we estimated alignment scores) are:

- CAT 1: Transportation infrastructure (built environment) alignment
- CAT 2: Land use policies alignment
- CAT 3: Transportation demand management policies alignment
- CAT 4: Cross-cutting issues policies alignment

Table 15. Alignment Scores (Category Breakdown and Overall Alignment)

| City | CAT 1 Score | CAT 2 Score | CAT 3 Score | CAT 4 Score | All Score |
|---------------|-------------|-------------|-------------|-------------|-----------|
| Oakland | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| San Francisco | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| San Jose | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Escondido | 59.46 | 75.37 | 92.11 | 83.86 | 68.13 |
| Fremont | 55.80 | 72.05 | 100.00 | 83.86 | 65.88 |
| Yuba City | 58.36 | 44.27 | 92.11 | 83.86 | 58.32 |
| Elk Grove | 54.16 | 48.16 | 92.11 | 83.86 | 57.33 |
| Sacramento | 62.99 | 81.61 | 92.11 | 4.19 | 55.85 |
| Oceanside | 62.14 | 75.37 | 100.00 | 0.00 | 53.32 |
| Oxnard | 55.45 | 44.27 | 0.00 | 95.81 | 52.16 |
| Lathrop | 55.45 | 44.27 | 0.00 | 95.81 | 52.16 |
| Poway | 55.45 | 44.27 | 0.00 | 95.81 | 52.16 |
| Live Oak | 55.45 | 44.27 | 0.00 | 95.81 | 52.16 |
| Half Moon Bay | 55.45 | 44.27 | 0.00 | 95.81 | 52.16 |
| Roseville | 58.36 | 81.61 | 64.27 | 0.00 | 50.51 |
| San Diego | 65.80 | 75.37 | 0.00 | 0.00 | 47.53 |
| Manteca | 61.87 | 53.66 | 100.00 | 0.00 | 46.73 |
| El Cajon | 59.90 | 53.66 | 92.11 | 0.00 | 45.12 |
| Santa Ana | 62.54 | 68.90 | 0.00 | 0.00 | 43.94 |
| Lodi | 59.65 | 44.27 | 100.00 | 0.00 | 42.80 |
| Tracy | 36.20 | 81.61 | 100.00 | 4.19 | 42.77 |
| Stockton | 36.20 | 81.61 | 100.00 | 0.00 | 41.93 |
| Riverside | 30.13 | 23.56 | 100.00 | 4.19 | 22.40 |
| Long Beach | 30.13 | 23.56 | 72.16 | 4.19 | 20.26 |
| Los Angeles | 0.00 | 0.00 | 100.00 | 4.19 | 0.00 |

The alignment scores were visualized in the maps below, Figures 1–5. Figure 1 displays a map with overall alignment score by city, and Figures 2–5 depict the category alignment score by city. Also, to access the web map, please use the following link: <https://arcg.is/1bKO140>.

Figure 1. Alignment Score Across All Categories For 25 Cities in California

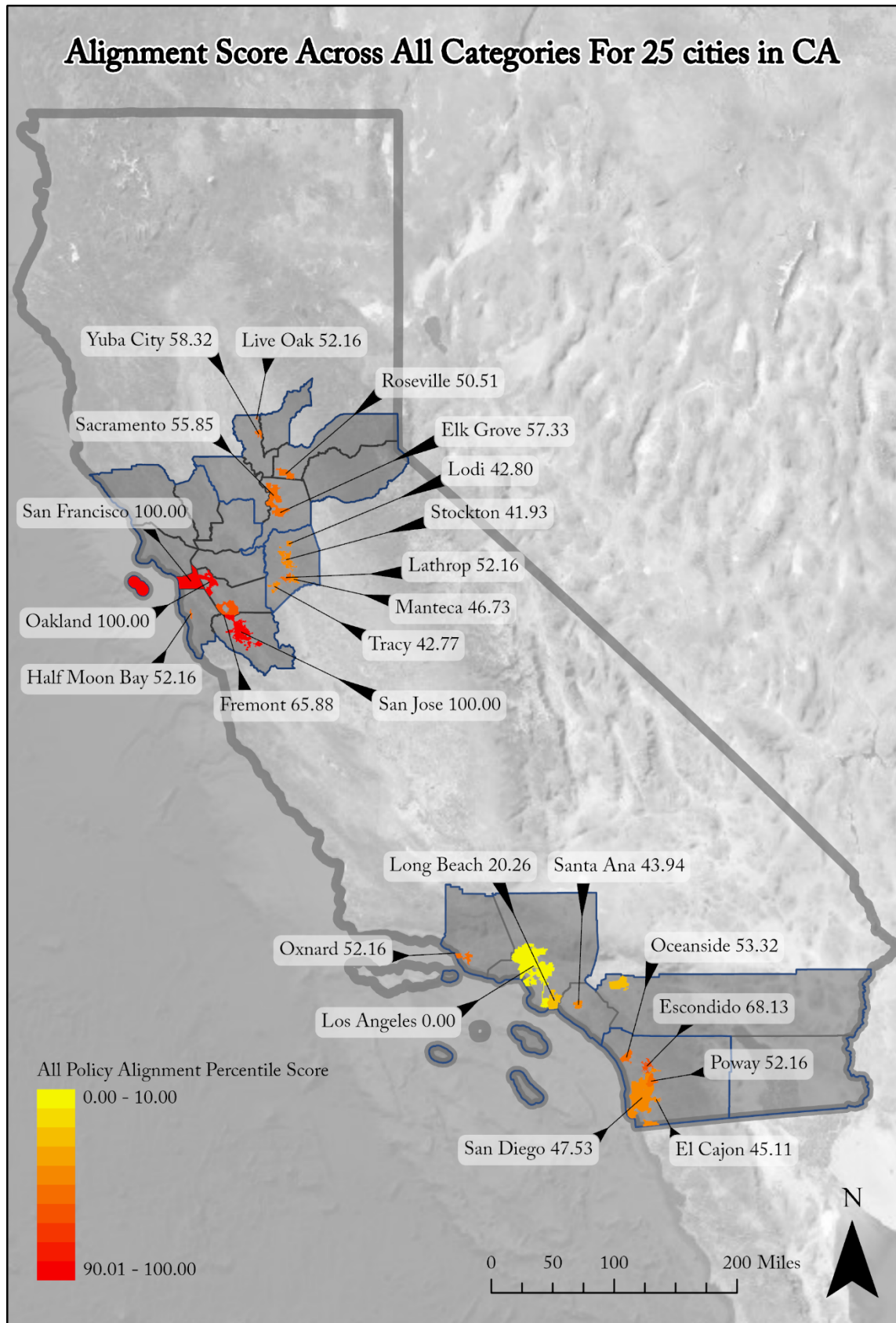


Figure 2. Transportation Policy (CAT 1) Alignment Score For 25 Cities in California

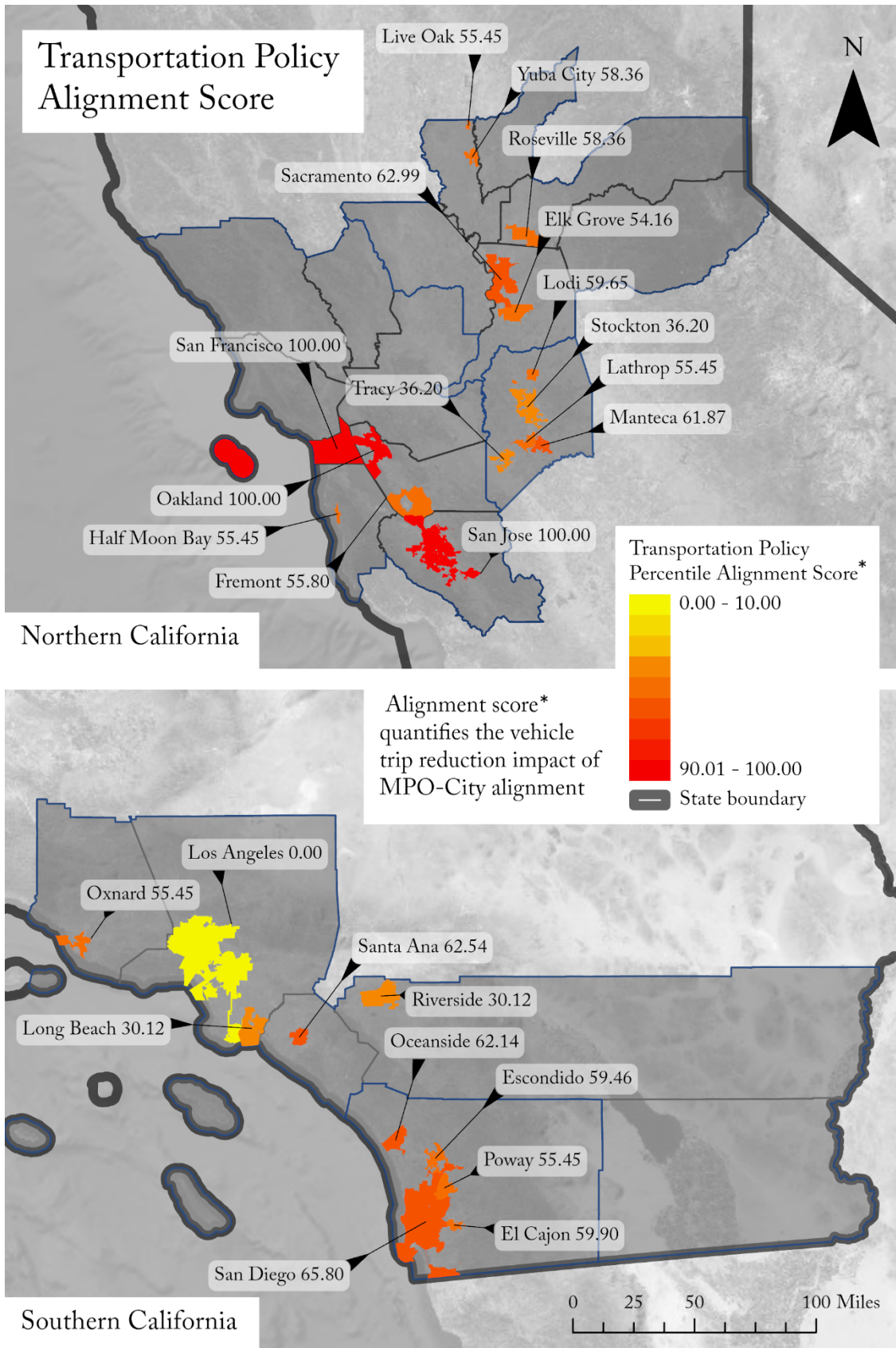


Figure 3. Land-use Policy (CAT 2) Alignment Score For 25 Cities in California

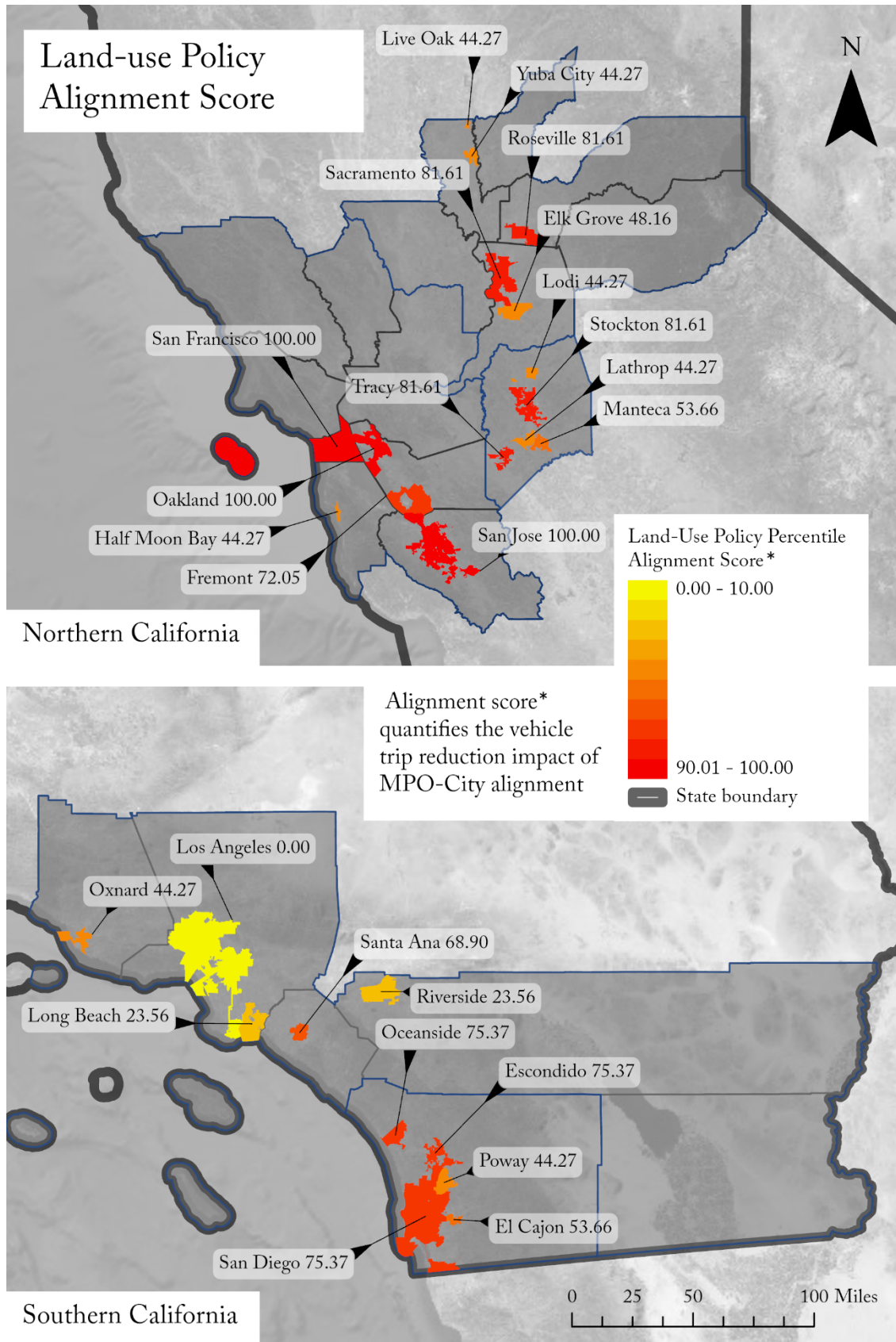


Figure 4. TDM Policy (CAT 3) Alignment Score For 25 Cities in California

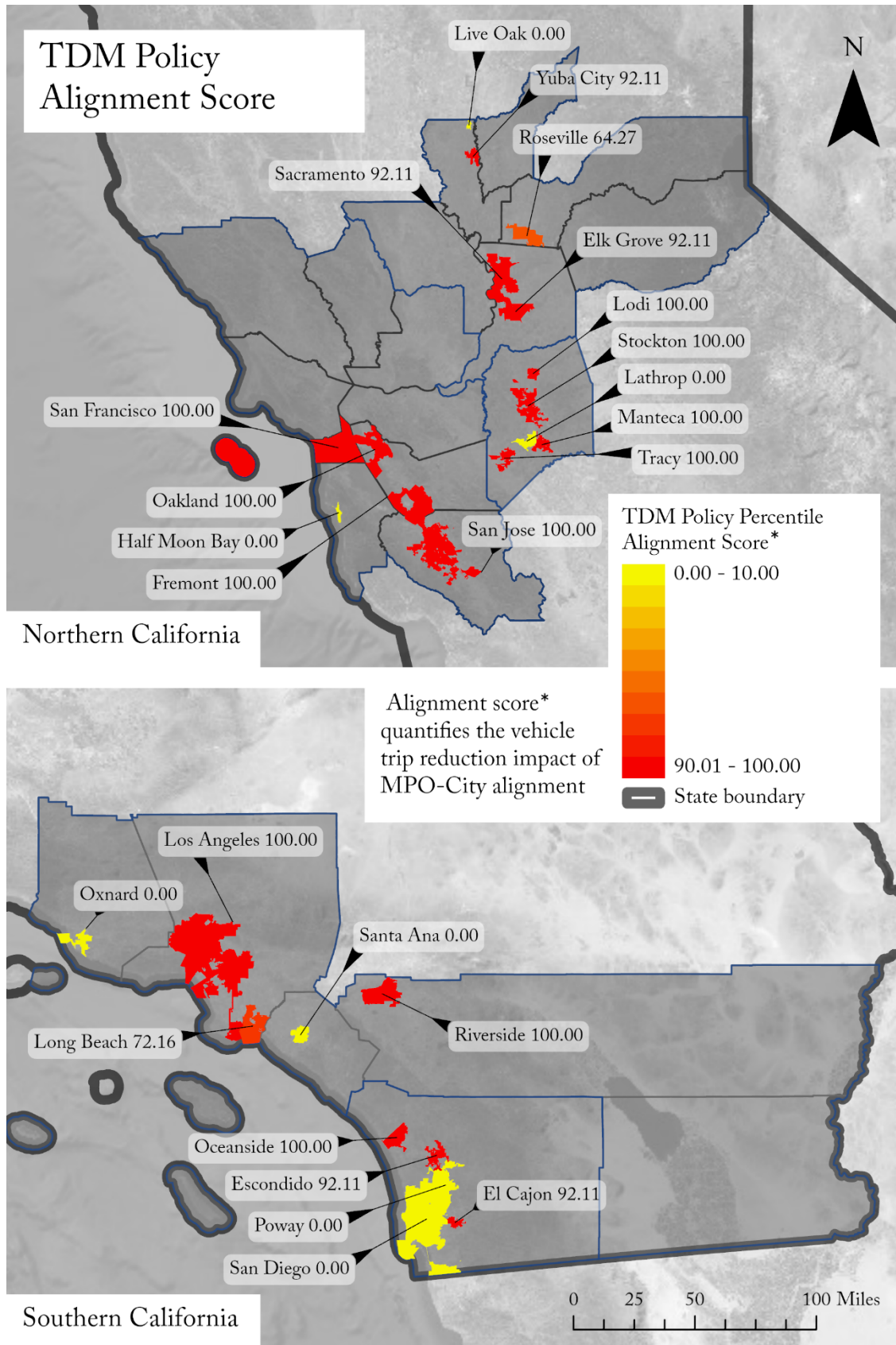
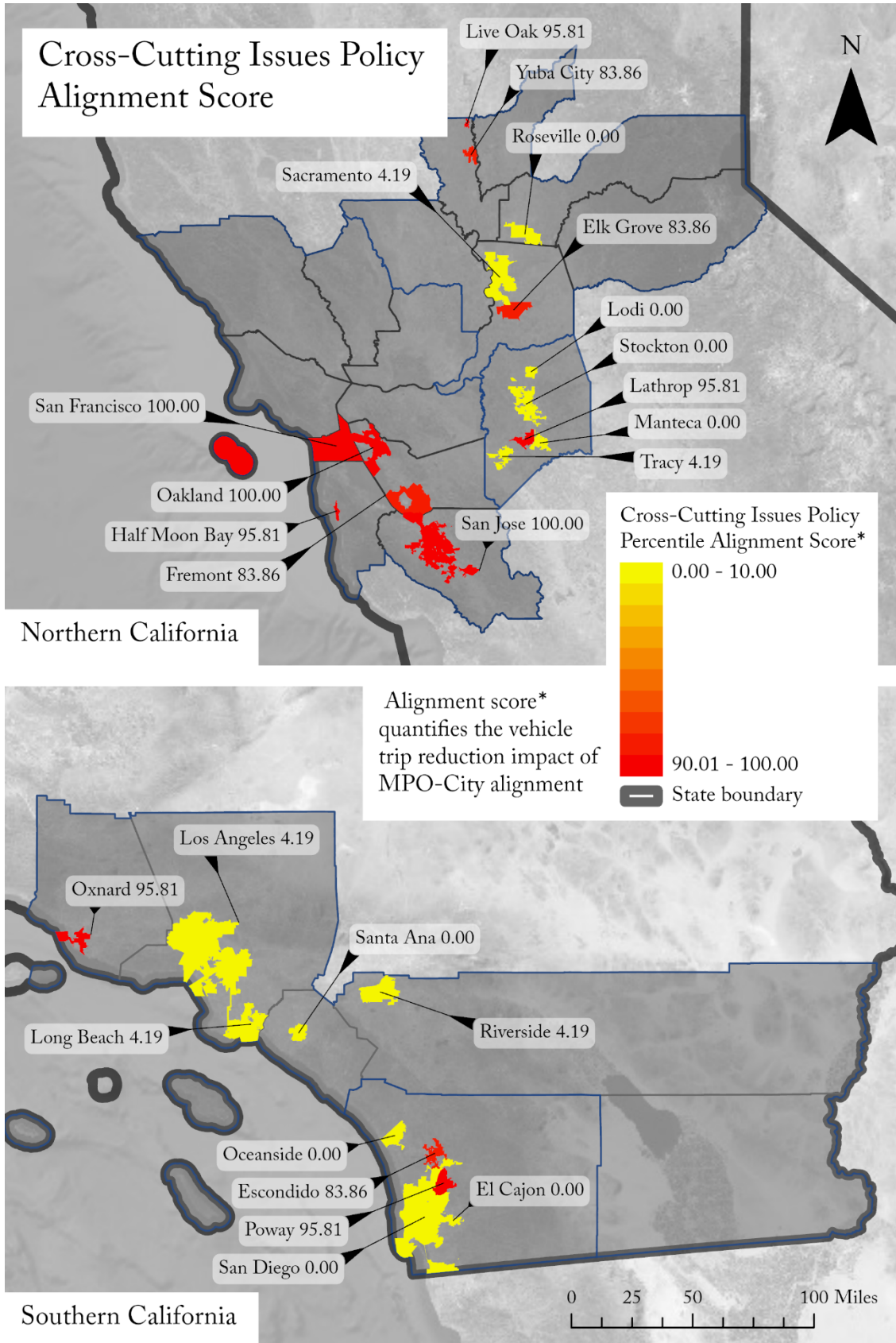


Figure 5. Cross-cutting Issues (CAT 3) Alignment Score For 25 Cities in California



As the alignment scores indicate, most of the Bay Area cities have a strong alignment with their MPOs. With Sacramento (Sacramento is a leader in its region, with a strong and well-aligned CAP, but more regional collaboration could improve local climate action planning in smaller cities in the region), the four major cities of Northern California, including Oakland, San Francisco, and San José, have the highest alignment scores for all the five categories including four strategies and one overall alignment: (1) Transportation infrastructure (built environment) alignment, (2) Land use policies alignment, (3) Transportation demand management policies alignment, (4) Cross-cutting issues policies alignment, as well as (5) the overall alignment.

More specifically, four of the top five cities for alignment in transportation infrastructure and built environment strategies are Oakland, San Francisco, San José, and Sacramento, located in Northern California and San Diego in Southern California. The bottom five in this category are Tracy, Stockton, Long Beach, Riverside, and Los Angeles. Since *Climate-Friendly Infrastructure*, *Mass Transit* and *Complete Street* policies demonstrate the highest weight values in Table 14, these categories of strategies are the most important in determining the alignment score of cities. In other words, cities receiving a high score most likely align their *Climate-Friendly Infrastructure*, *Mass Transit*, and *Complete Street* strategies with their MPOs, whereas the cities receiving a low score possibly have limited alignment for such policies with their MPOs. In terms of land use policies, the most well-aligned strategies are those of the cities of Oakland, San Francisco, San José, Sacramento, and Roseville; whereas the cities of Live Oak, Half Moon Bay (neither of which has a local CAP), Long Beach, Riverside, and Los Angeles demonstrate the most limited alignment. In this category, according to Table 14, *Preserve Open-Space* and *Parking Requirements* strategies play a key role, and hence the alignment in these categories could lead Oakland, San Francisco, San José, Sacramento, and Roseville to achieve a higher score.

As for TDM strategies, there is a small variation among alignment scores, hence most of the cities are found to have a strong alignment. According to Table 14, among the four strategies included in this section, only TDM strategies could drive the variation in this score, and thus the results indicate that most cities are well aligned for TDM strategies with their MPOs. However, the cities of San Diego, Santa Ana, Oxnard, Lathrop, Poway, Live Oak, and Half Moon Bay have the lowest alignment scores in TDM strategies (note that Oxnard, Poway, Live Oak, Half Moon Bay, and Lathrop have not developed a CAP yet). As for cross-cutting issues, we found a clear divide, with half of the cities' alignments with MPOs ranging between 83 and 100, and the remaining cities having alignment scores of less than five. However, in this category, Oakland, San Francisco, San José, are at the top in terms of alignment.

The San Joaquin region's cities, adjacent to and economically tied to the Bay Area, exhibit limited alignment with SJCOG. The region's economic dependence and subordinate relation to the surrounding areas, along with the fact that the primary economic driver is goods movement, might explain the lag in climate action planning and intra-regional coordination.

On the other hand, most CAPs developed by major cities in Southern California's SCAG region, the nation's largest MPO (such as Long Beach, Riverside, or Los Angeles), demonstrate limited

alignment with their MPO's SCS. It is important to note that the min-max normalization method used in this research assigns a value "0" to the minimum raw value. In other words, the value 0 is not 0 per se, and is simply the minimum value converted to 0.²³ For instance, in the case of Los Angeles, the value 0 does not mean no alignment, but just that Los Angeles has the minimum alignment value. This low value is also the case because in addition to few CAP-SCS alignments, those alignments are mostly for the strategies that have low weights according to the t-values estimated in our regression models. On the contrary, in the one-county SANDAG, the largest city, San Diego's CAP, has a solid alignment for the first two categories: (1) Transportation infrastructure (built environment) alignment and (2) Land use policies alignment. The exception to this trend is alignment for TDM strategies, where both Southern California cities (Long Beach, Riverside, and Los Angeles) and Bay Area cities (Oakland, San Francisco, and San Jose) demonstrate a strong alignment with regional strategies.

The overall alignment score has a strong variation across the 25 cities, where among the top five are Bay Area cities including Oakland, San Francisco, San José, and Fremont, as well as Escondido in Southern California. The cities of Tracy, Stockton, Riverside, Long Beach, and Los Angeles demonstrate the most limited alignment of strategies with their regional SCSs.

5. Conclusions and Discussion of Major Findings

This chapter synthesizes the major findings and conclusions from qualitative and quantitative analysis of local climate action plans (CAPs) and regional Sustainable Communities Strategies (SCSs) and their alignment. It also offers policy recommendations to help reduce GHG emissions from transportation.

The patterns of local and regional climate policy are diverse across the state, but poor alignment is not necessarily a sign of limited climate action at the local level. Most Bay Area local policies have a strong alignment with regional strategies. In addition to the Bay Area's highest alignment score across categories, the four major cities of Northern California, Oakland, San Francisco, San José, and Sacramento, have the highest alignment scores for all four strategy categories of transportation infrastructure: (1) built environment, (2) land use policies, (3) transportation demand management, (4) cross-cutting issues policies, as well as overall alignment.

The San Joaquin region cities, adjacent to and economically tied to the Bay Area, exhibit relatively limited alignment with SJCOG. The region's economic makeup and its dependence on the Bay Area might explain the lag in climate action planning and intra-regional coordination. Almost 60,000 San Joaquin County residents travel to the Bay Area for work regularly, which has resulted in county residents driving 219 more miles per capita in 2018 than other California residents.²⁴ Regional strategies to address the jobs-housing imbalance and improve public transportation can help alleviate this problem, but local governments in the region need additional support to better align their policies with regional actions.

The patterns of local and regional climate policy alignment in Southern California are more diverse. On the one hand, San Diego's CAP demonstrates solid alignment with the one-county SANDAG's SCS for the two key categories of transportation infrastructure policies and land use policies. On the other hand, major cities in the SCAG region (e.g., Los Angeles, Long Beach, and Riverside) demonstrate limited alignment with their MPO's SCS. Considering that SCAG is the largest MPO in the nation, and represents six counties and 191 cities, it is not surprising that regional coordination is more complex. Large and dominant cities in these regions can either lead the regional efforts or focus more on the success of their local strategies. Small cities with constrained resources, limited transportation services, and dependence on large cities, might be either reluctant to participate in regional efforts or otherwise rely more on regional efforts.

Last, there is a clear pattern of TDM strategies aligning at local and regional levels in both Southern California cities (Long Beach, Riverside, and Los Angeles) and Bay Area cities (Oakland, San Francisco, and San José). This could be because TDM strategies, unlike transportation infrastructure or land use strategies, are more standard. There are clear best practices for TDM strategies with evidence of success in different contexts and geographic areas. Land use

and transportation infrastructure strategies are more diverse and highly context sensitive, requiring local governments to further analyze the appropriateness of common strategies for their communities.

It is important to note that the lack of policy alignment at regional and local levels is not necessarily a sign of limited climate action or failure of local climate strategies for a number of reasons. First, alignment is measured in relative (not absolute) values. Second, limited alignment could also be a sign of strong independent local action. For example, Los Angeles has developed a robust and unique climate action plan that diverges from broader regional efforts. Conversely, large dominant cities can lead regional efforts, and, as a result, we can see higher alignment of local plans from these cities with their regional SCSs. Third, local action (independent of regional efforts) can be effective in reducing vehicle trips, and by extension, the GHG emissions associated with it. Last, the alignment score estimated here is composed of weighted factors. There could be alignment in strategies that have negative weights, reducing the overall value.

Active transportation strategies are the most commonly found strategies in regional and municipal climate action plans that effectively reduce vehicle trips. Most of the analyzed cities and MPOs have a complete streets strategy, as well as other specific strategies, to encourage biking and walking. Although active transportation policy actions generally fall under a complete streets strategy umbrella, many cities prefer also to focus on specific active transportation strategies in their CAPs. There is a wide range of policy actions related to complete streets, which are well supported by regional and state legislative, planning and funding efforts. Moreover, the results of the quantitative analysis indicate that active transportation strategies effectively reduce vehicle trips, especially if the MPO and the local action align.

Analyzed cities and regions consistently plan for densification and land use diversity. Most of the cities and MPOs have TOD and infill development strategies, as well as strategies to improve jobs-housing balance and plan for new housing near activity centers. Like active transportation strategies, the densification and land use diversification strategies are vertically integrated through the levels of government. Infill development and TOD strategies mostly stem from regional plans and are implemented through the area and specific plans that have planning and funding support from regional agencies. Infill development policies have the greatest alignment impact score, although the alignment impact of all of these four strategies is positive. Because population growth can result in increased vehicle trips (as expected, and demonstrated by our analysis), TODs and other pedestrian-oriented developments can help change travel behavior in favor of environmentally friendly modes of transportation.

Policies that aim to improve mass transit networks and ridership are the most effective in reducing vehicle trips, though the scope and types of these policies differ between larger and smaller cities. Well-aligned regional and local active mass transit strategies are effective in reducing auto-trips. Furthermore, larger cities have more leverage in planning and designing mass transit systems and their efforts often pertain to improving the transit infrastructure and routing. Smaller cities are commonly in a position to plan around the regional transit operators' plans and focus on the

policies that supplement the existing network by incentivizing, promoting, and subsidizing mass transit. Smaller cities often update the design guidelines in areas close to transit stops and hubs, supplement the network by city-operated shuttle service, or facilitate technological services that improve transit use experience.

Well-aligned regional and local level climate-friendly infrastructure appear to have the most significant impact on vehicle-trip reduction, on average a seven percent decrease in vehicle trips. The most effective group of strategies in the Transportation infrastructure/Built Environment category, is climate-friendly infrastructure. The purpose of climate-friendly infrastructure is to help mitigate GHG emissions and simultaneously provide resilience against climate impacts, such as flooding and heat waves. Climate-friendly infrastructure strategies have a wide range, from installing solar panels and LED lighting to preserving tree canopy cover. With much focus on planting trees, preserving green spaces, and building well-lit sidewalks, climate-friendly infrastructure can also provide an aesthetically pleasing and comfortable walking and biking environment.

Many local level strategies alone, such as strategies for goods movement, urban forest strategies, parking requirements, and education and outreach programs, are effective in vehicle-trip reduction. Although the alignment of regional and local action to reduce vehicle trips is key for the effectiveness of some strategies, findings from this research stress the importance of local action. For example, the effectiveness of TDM strategies for reducing vehicle trips depends on the level of alignment between regional and local efforts, but local action is more important for community engagement and outreach for TDM strategies. Similarly, local parking policies and urban forest strategies are effective in vehicle trip reduction regardless of how well these strategies align with regional efforts.

Built-environmental factors, such as density, land use diversity, walkability, and a strong transit system are all significant indicators of increase in non-auto commute. As expected, the built environment plays a key role in commute patterns and, by extension, the vehicle trip reduction during a ten-year period. According to our model, density, land use diversity, walkability, and a strong transit system are all significant indicators of increase in non-auto commuting across the block groups in the 25 cities in our sample. Among all the built environmental factors, we found that density and walkability have a stronger correlation once we take the t-stats into account. However, in terms of coefficient values, transit quality has a relatively higher value. Specifically, one unit increase in transit frequency per capita in a block group, correlates with an average of 39% increase in non-auto commuting between 2010 and 2019.

Job-housing balance strategies should be coupled with adequate transit access to effectively impact vehicle trips; otherwise, vehicle trips will increase as the population increases. The results of this study show that population is an important indicator of increased vehicle trips. One interesting finding is that population increase in areas with a significant active commute pattern in 2010 resulted in increased vehicle trips in 2019. This finding suggests that strategies to address job-housing imbalance (i.e., building housing near employment centers) can potentially increase

vehicle trips, unless people find public transportation or active modes of transportation an attractive alternative to driving. This aligns well with another finding, that ADU programs can have a negative impact on vehicle trip reduction. ADU strategies are meant to increase density and provide affordable housing in areas with high housing demand. Although increasing urban density in areas with sufficient public and active transportation infrastructure can boost transit ridership and active transportation participation, density in sprawled areas with limited transit access will increase vehicle trips. As such, local and regional governments developing strategies to address the housing demand should simultaneously focus on access to transit and other transportation modes to lessen driving.

Key Takeaway

A key takeaway from this research is that although local and regional climate policy alignment can be crucial for successfully reducing vehicle trips, local action is equally important. Although there are established best practices for climate action planning, there is no one-size-fits-all approach to reducing transportation emissions. Regional SCSs often use best practices and analysis of regional context to develop climate strategies; municipal CAPs are developed and implemented to address local needs. Some cities have a longer history of climate planning and, by extension, the capacity to take innovative action to address transportation emissions and even lead regional climate efforts. Others are just starting the process of developing a CAP and require more technical and financial support from the regional and state governments. Also, the results of this research show that while alignment of regional and local policies is important in some areas, local action can be more effective in others. Specifically, strategies to engage communities in climate planning or policies to address local problems, such as parking, can be more successful at the local level. Therefore, the State of California should support both local and regional action to address transportation emissions.

Limitations of the Study and Directions for Future Research

This study has two major limitations. First, the research team used vehicle trip reduction as the dependent variable due to the lack of consistent and comparable VMT data at the block group level. Yet, VMT is a better measure of climate planning success since there is overwhelming evidence in the literature that as VMT increases, GHG emissions rise. Cities and MPOs use different VMT estimation tools, which means that their results cannot be compared across the state. Second, despite our efforts to collect data from a representative sample of cities and regions in California, it is likely that there are additional patterns in local and regional alignment of climate policy across the state which our analysis has not captured. Availability of VMT data at a more granular level can open up the potential for new studies to investigate the impact of local and regional climate policy alignment on transportation emissions. Future studies can also investigate how rural communities are coordinating their efforts regionally and how the state government can boost the success of these efforts.

Appendix A

Transportation Infrastructure / Built Environment

Table 1. Regression Results Table for Variable Bike Alignment (Bikealig)

| | | | | | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|------------|
| Linear regression | | | Number of obs | 5,080 | | |
| | | | F(11,5068) | 75.47 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2052 | | |
| | | | Root MSE | 10.447 | | |
| nonautopct_cge-19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| bikealig | 0.316508 | 0.739996 | 0.43 | 0.669 | -1.134204 | 1.76722 |
| nonautoctw_pct_10 | -29.5715 | 1.925819 | -15.36 | 0 | -33.34694 | -25.79606 |
| pct30mnCTW | -0.090201 | 0.0109556 | -8.23 | 0 | -0.1116782 | -0.0687228 |
| totpop | -0.00025 | 0.000166 | -1.51 | 0.132 | -0.0005753 | 0.0000753 |
| perc45t064 | -0.178429 | 0.0280052 | -6.37 | 0 | -0.2333311 | -0.1235264 |
| percemployed | -0.120204 | 0.0375948 | -3.2 | 0.001 | -0.1939061 | -0.0465018 |
| baandaboveperc | 0.143558 | 0.0073274 | 19.59 | 0 | 0.1291927 | 0.1579226 |
| act den | 0.051541 | 0.0139851 | 3.69 | 0 | 0.0241245 | 0.0789581 |
| Emp_Ent | 0.697277 | 0.6308935 | 1.11 | 0.269 | -0.5395466 | 1.934101 |
| RdDen | 0.120585 | 0.0209696 | 5.75 | 0 | 0.0794755 | 0.1616944 |
| TransFq_pCap | 37.16633 | 17.45072 | 2.13 | 0.033 | 2.95538 | 71.37728 |
| _cons | 14.94487 | 3.775658 | 3.96 | 0 | 7.542953 | 22.3468 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.63 | 0.61339 | | | | |
| act den | 1.43 | 0.701754 | | | | |
| TransFq_pCap | 1.23 | 0.813274 | | | | |
| baandabover~c | 1.16 | 0.860298 | | | | |
| RdDen | 1.15 | 0.86777 | | | | |
| totpop | 1.14 | 0.875585 | | | | |
| perc45t064 | 1.13 | 0.888237 | | | | |
| pct30mnCTW | 1.09 | 0.917947 | | | | |
| percemployed | 1.09 | 0.918049 | | | | |
| bikealig | 1.07 | 0.930887 | | | | |
| Emp_Ent | 1.03 | 0.96946 | | | | |
| Mean VIF | 1.2 | | | | | |
| end of do-file | | | | | | |

Table 2. Regression Results Table for Variable Pedestrian Infrastructure Alignment (Pedalig)

| Linear regression | | Number of obs | 5,080 | | | |
|-------------------|-------------|------------------|--------|-------|----------------------|------------|
| | | F(11, 5068) | 75.47 | | | |
| | | Prob > F | 0.0000 | | | |
| | | R-squared | 0.2052 | | | |
| | | Root MSE | 10.447 | | | |
| nonautoptcge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| pedalig | 0.3165079 | 0.739996 | 0.43 | 0.669 | -1.134204 | 1.76722 |
| nonautoctw_pct_10 | -29.5715 | 1.925819 | -15.36 | 0 | -33.34694 | -25.79606 |
| pct30mnCTW | -0.0902005 | 0.0109556 | -8.23 | 0 | -0.1116782 | -0.0687228 |
| totpop | -0.00025 | 0.000166 | -1.51 | 0.132 | -0.0005753 | 0.0000753 |
| perc45t064 | -0.1784288 | 0.0280052 | -6.37 | 0 | -0.2333311 | -0.1235264 |
| percemployed | -0.1202039 | 0.0375948 | -3.2 | 0.001 | -0.1939061 | -0.0465018 |
| baandaboveperc | 0.1435576 | 0.0073274 | 19.59 | 0 | 0.1291927 | 0.1579226 |
| act_den | 0.0515413 | 0.0139851 | 3.69 | 0 | 0.0241245 | 0.0789581 |
| Emp_Ent | 0.6972773 | 0.6308935 | 1.11 | 0.269 | -0.5395466 | 1.934101 |
| RdDen | 0.120585 | 0.0209696 | 5.75 | 0 | 0.0794755 | 0.1616944 |
| TransFq_pCap | 37.16633 | 17.45072 | 2.13 | 0.033 | 2.95538 | 71.37728 |
| _cons | 14.94487 | 3.775658 | 3.96 | 0 | 7.542953 | 22.3468 |
| vif Variable | VIF | I/VIF | | | | |
| nonautoct~10 | 1.63 | 0.61339 | | | | |
| act_den | 1.43 | 0.701754 | | | | |
| TransFq_pCap | 1.23 | 0.813274 | | | | |
| baandabove~c | 1.16 | 0.860298 | | | | |
| RdDen | 1.15 | 0.86777 | | | | |
| totpop | 1.14 | 0.875585 | | | | |
| perc45t064 | 1.13 | 0.888237 | | | | |
| percemployed | 1.09 | 0.917947 | | | | |
| pct30mnCTW | 1.09 | 0.918049 | | | | |
| pedalig | 1.07 | 0.930887 | | | | |
| Emp_Ent | 1.03 | 0.96946 | | | | |
| Mean VIF | 1.2 | | | | | |

Table 3. Regression Results Table for Variable Complete Streets Alignment (Complstalig)

| | | | | | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|------------|
| Linear regression | | | Number of obs | 5,080 | | |
| | | | F(11, 5068) | 75.93 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2057 | | |
| | | | Root MSE | 10.444 | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| complstalig | 0.7535711 | 0.3383414 | 2.23 | 0.026 | 0.0902757 | 1.416867 |
| nonautoctw_pct_10 | -29.72337 | 1.916884 | -15.51 | 0 | -33.48129 | -25.96545 |
| pct30mnCTW | -0.0876161 | 0.0107391 | -8.16 | 0 | -0.1086695 | -0.0665628 |
| totpop | -0.0002233 | 0.0001641 | -1.36 | 0.174 | -0.000545 | 0.0000984 |
| perc45t064 | -0.1788733 | 0.0279779 | -6.39 | 0 | -0.2337221 | -0.1240245 |
| percemployed | -0.1164822 | 0.0377356 | -3.09 | 0.002 | -0.1904604 | -0.0425041 |
| baandaboveperc | 0.1420135 | 0.0073396 | 19.35 | 0 | 0.1276246 | 0.1564024 |
| act den | 0.0513325 | 0.0139457 | 3.68 | 0 | 0.0239929 | 0.0786722 |
| Emp_Ent | 0.7039196 | 0.6305249 | 1.12 | 0.264 | -0.5321816 | 1.940021 |
| RdDen | 0.1176866 | 0.0209687 | 5.61 | 0 | 0.0765789 | 0.1587943 |
| TransFq_pCap | 37.06029 | 17.33974 | 2.14 | 0.033 | 3.066895 | 71.05368 |
| _cons | 14.27567 | 3.688609 | 3.87 | 0 | 7.044399 | 21.50693 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.64 | 0.609101 | | | | |
| act den | 1.43 | 0.701043 | | | | |
| TransFq_pCap | 1.23 | 0.813221 | | | | |
| baandabove~c | 1.18 | 0.8499 | | | | |
| RdDen | 1.16 | 0.86162 | | | | |
| totpop | 1.14 | 0.874555 | | | | |
| complstalig | 1.14 | 0.877826 | | | | |
| perc45t064 | 1.13 | 0.888208 | | | | |
| percemployed | 1.09 | 0.913857 | | | | |
| pct30mnCTW | 1.08 | 0.923387 | | | | |
| Emp_Ent | 1.03 | 0.969539 | | | | |
| Mean VIF | 1.28 | | | | | |

Table 4. Regression Results Table for Variable Electric Vehicle Alignment (Evalig)

| Linear regression | | Number of obs | 5,080 | | | |
|-------------------|-------------|------------------|--------|-------|----------------------|------------|
| | | F(11, 5068) | 75.83 | | | |
| | | Prob > F | 0 | | | |
| | | R-squared | 0.2053 | | | |
| | | Root MSE | 10.447 | | | |
| nonautopct_cg~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| evalig | -0.2777 | 0.4239383 | -0.66 | 0.512 | -1.108802 | 0.5534023 |
| nonautoctw_pct_10 | -29.5214 | 1.927696 | -15.31 | 0 | -33.30051 | -25.74228 |
| pct30mnCTW | -0.092106 | 0.0112609 | -8.18 | 0 | -0.114182 | -0.0700296 |
| totpop | -0.000261 | 0.000165 | -1.58 | 0.114 | -0.0005846 | .0000625 |
| perc45t064 | -0.178159 | 0.028029 | -6.36 | 0 | -0.2331082 | -0.1232104 |
| percemployed | -0.120238 | 0.0376214 | -3.2 | 0.001 | -0.1939919 | 0.0464835 |
| baandaboveperc | 0.14451 | 0.007522 | 19.21 | 0 | 0.129764 | 0.1592568 |
| act den | 0.051547 | 0.0139885 | 3.68 | 0 | 0.0241231 | 0.0789703 |
| Emp_Ent | 0.684714 | 0.6306606 | 1.09 | 0.278 | -0.5516536 | 1.921081 |
| RdDen | 0.120847 | 0.0209584 | 5.77 | 0 | 0.0797596 | 0.1619346 |
| TransFq_pCap | 37.17575 | 17.4584 | 2.13 | 0.033 | 2.949742 | 71.40175 |
| _cons | 15.57605 | 3.657598 | 4.26 | 0 | 8.40558 | 22.74653 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.64 | 0.610217 | | | | |
| act den | 1.42 | 0.701823 | | | | |
| TransFq_pCap | 1.23 | 0.813263 | | | | |
| baandabove~c | 1.22 | 0.821137 | | | | |
| evalig | 1.21 | 0.828204 | | | | |
| RdDen | 1.15 | 0.866668 | | | | |
| totpop | 1.14 | 0.879745 | | | | |
| pct30mnCTW | 1.13 | 0.884767 | | | | |
| perc45t064 | 1.13 | 0.887397 | | | | |
| percemployed | 1.09 | 0.918177 | | | | |
| Emp_Ent | 1.03 | 0.968396 | | | | |
| Mean VIF | 1.22 | | | | | |

Table 5. Regression Results Table for Variable Ride Sharing Alignment (Ridesharelig)

| Linear regression | | Number of obs | 5,080 | | | |
|-------------------|-------------|------------------|--------|-------|----------------------|------------|
| | | F(11, 5068) | 75.77 | | | |
| | | Prob > F | 0 | | | |
| | | R-squared | 0.2053 | | | |
| | | Root MSE | 10.447 | | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| ridesharelig_1 | -0.2204402 | 0.2685783 | -0.82 | 0.412 | -0.7469698 | 0.3060894 |
| nonautoctw_pct_10 | -29.51195 | 1.924427 | -15.34 | 0 | -33.28466 | -25.73924 |
| pct30mnCTW | -0.0924049 | 0.0112811 | -8.19 | 0 | -0.1145208 | -0.070289 |
| totpop | -0.0002598 | 0.0001647 | -1.58 | 0.115 | -0.0005827 | 0.0000632 |
| perc45t064 | -0.1780798 | 0.0280343 | -6.35 | 0 | -0.2330391 | -0.1231205 |
| percemployed | -0.1194709 | 0.0377332 | -3.17 | 0.002 | -0.1934442 | -0.0454976 |
| baandaboveperc | 0.1445329 | 0.0074546 | 19.39 | 0 | 0.1299186 | 0.1591472 |
| act den | 0.0515837 | 0.0140035 | 3.68 | 0 | 0.0241308 | 0.0790367 |
| Emp_Ent | 0.6809475 | 0.6305101 | 1.08 | 0.28 | -0.5551249 | 1.91702 |
| RdDen | 0.1214066 | 0.0210044 | 5.78 | 0 | 0.0802289 | 0.1625844 |
| TransFq_pCap | 37.13428 | 17.45026 | 2.13 | 0.033 | 2.924239 | 71.34432 |
| _cons | 15.6542 | 3.638664 | 4.3 | 0 | 8.520847 | 22.78755 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.64 | 0.610247 | | | | |
| act den | 1.43 | 0.701695 | | | | |
| TransFq_pCap | 1.23 | 0.813244 | | | | |
| baandabove~c | 1.2 | 0.835811 | | | | |
| ridesharelig_1 | 1.19 | 0.837413 | | | | |
| RdDen | 1.16 | 0.862241 | | | | |
| totpop | 1.13 | 0.882809 | | | | |
| pct30mnCTW | 1.13 | 0.886961 | | | | |
| perc45t064 | 1.13 | 0.887398 | | | | |
| percemployed | 1.09 | 0.916311 | | | | |
| Emp_Ent | 1.03 | 0.968159 | | | | |
| Mean VIF | 1.21 | | | | | |

Table 6. Regression Results Table for Variable Low-Carbon Fuels Alignment (Lowcarbalig)

| | | | | | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|------------|
| Linear regression | | | Number of obs | 5,080 | | |
| | | | F(11, 5068) | 76.13 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2052 | | |
| | | | Root MSE | 10.447 | | |
| nonautopct_cgew19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| lowcarbalig | 0.1079651 | 0.4075462 | 0.26 | 0.791 | -0.6910017 | 0.9069319 |
| nonautoctw_pct_10 | -29.57783 | 1.909467 | -15.49 | 0 | -33.32122 | -25.83445 |
| pct30mnCTW | -0.0899144 | 0.0117416 | -7.66 | 0 | -0.1129329 | -0.0668959 |
| totpop | -0.0002545 | 0.0001645 | -1.55 | 0.122 | -0.0005769 | 0.0000679 |
| perc45t064 | -0.1786578 | 0.0280588 | -6.37 | 0 | -0.2336651 | -0.1236505 |
| percemp10yed | -0.1209084 | 0.0378657 | -3.19 | 0.001 | -0.1951415 | -0.0466753 |
| baandaboveperc | 0.1435898 | 0.0073259 | 19.6 | 0 | 0.1292279 | 0.1579517 |
| act_den | 0.0514978 | 0.0140356 | 3.67 | 0 | 0.0239819 | 0.0790136 |
| Emp_Ent | 0.6951046 | 0.6307062 | 1.1 | 0.27 | -0.5413522 | 1.931561 |
| RdDen | 0.1202277 | 0.0209217 | 5.75 | 0 | 0.0792122 | 0.1612431 |
| TransFq_pCap | 37.14595 | 17.44426 | 2.13 | 0.033 | 2.947668 | 71.34424 |
| _cons | 15.23957 | 3.634378 | 4.19 | 0 | 8.114618 | 22.36452 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoctN10 | 1.64 | 0.610625 | | | | |
| act_den | 1.43 | 0.698813 | | | | |
| lowcarbalig | 1.25 | 0.797166 | | | | |
| TransFq_pCap | 1.23 | 0.8132K | | | | |
| pct30mnCTl,l | 1.2 | 0.831619 | | | | |
| baandabove~c | 1.16 | 0.858588 | | | | |
| RdDen | 1.16 | 0.864209 | | | | |
| totpop | 1.13 | 0.884676 | | | | |
| perc45t064 | 1.13 | 0.887112 | | | | |
| percemp10yed | 1.1 | 0.912104 | | | | |
| Emp_Ent | 1.03 | 0.969604 | | | | |
| Mean VIF | 1.22 | | | | | |

Table 7. Regression Results Table for Variable Autonomous Vehicles Alignment (Avalig)

| Linear regression | | | Number of obs | 5,080 | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|------------|
| | | | F(11, 5068) | 92.54 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2549 | | |
| | | | Root MSE | 10.116 | | |
| nonautopct_cgeN19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| avalig | -5.540793 | 0.3312977 | -16.72 | 0 | -6.190279 | -4.891306 |
| nonautoctw_pct_10 | -33.54613 | 2.127772 | -15.77 | 0 | -37.71748 | -29.37478 |
| pct30mnCTW | -0.1369528 | 0.0114482 | -11.96 | 0 | -0.1593961 | -0.1145094 |
| totpop | -0.0002836 | 0.0001706 | -1.66 | 0.697 | -0.0006181 | 0.0000509 |
| perc45t064 | -0.1750564 | 0.6275736 | -6.35 | 0 | -0.2291126 | -0.1210002 |
| percemp10yed | -0.1346007 | 0.0381333 | -3.53 | 0 | -0.2093585 | -0.0598429 |
| baandaboveperc | 0.1402752 | 0.0070156 | 19.99 | 0 | 0.1265216 | 0.1540287 |
| act den | 0.0558263 | 0.0155199 | 3.6 | 0 | 0.0254005 | 0.086252 |
| Emp_Ent | 1.00096 | 0.6169847 | 1.62 | 9.105 | -0.2085968 | 2.210516 |
| RdDen | 0.1492037 | 0.0206926 | 7.21 | 0 | 0.1086372 | 0.1897702 |
| TransFq_pCap | 36.55896 | 17.25701 | 2.12 | 0.034 | 2.727753 | 70.39017 |
| _cons | 21.72988 | 3.66571 | 5.93 | 0 | 14.54351 | 28.91626 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoctN10 | 1.71 | 0.585076 | | | | |
| act den | 1.43 | 0.698916 | | | | |
| TransFq_pCap | 1.23 | 0.813259 | | | | |
| RdDen | 1.16 | 0.861475 | | | | |
| baandabover~c | 1.15 | 0.868373 | | | | |
| totpop | 1.13 | 0.884749 | | | | |
| perc45t064 | 1.13 | 0.888231 | | | | |
| pct30mnCTW | 1.12 | 0.892924 | | | | |
| avalig | 1.12 | 0.895982 | | | | |
| percemp10yed | 1.09 | 0.917615 | | | | |
| Emp_Ent | 1.03 | 0.968842 | | | | |
| Mean VIF | 1.21 | | | | | |

Table 8. Regression Results Table for Variable Climate-Friendly Infrastructure Alignment (Climalig)

| Linear regression | | | Number of obs | 5,080 | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|-------------|
| | | | F(11, 5068) | 98.11 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2618 | | |
| | | | Root MSE | 10.069 | | |
| nonautopct_cg~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| clmalig | 7.188128 | 0.4224629 | 17.01 | 0.000 | 6.359918 | 8.016338 |
| nonautoctw_pct_10 | -34.94133 | 1.987726 | -17.58 | 0 | -38.83813 | -31.04453 |
| pct30mnCTW | -0.0709271 | 0.0104521 | -6.79 | 0 | -0.0914178 | -0.0504364 |
| totpop | -0.0003308 | 0.0001657 | -2 | 0.046 | -0.0006557 | -0.00000584 |
| perc45t064 | -0.2064419 | 0.0269949 | -7.65 | 0 | -0.2593636 | -0.1535201 |
| percemployed | -0.1639812 | 0.0374421 | -4.38 | 0 | -0.237384 | -0.0905784 |
| baandaboveperc | 0.1086292 | 0.0071005 | 15.3 | 0 | 0.0947092 | 0.1225492 |
| act den | 0.0517949 | 0.0142766 | 3.63 | 0 | 0.0238065 | 0.0797832 |
| Emp_Ent | 1.243296 | 0.6127758 | 2.03 | 0.043 | 0.0419904 | 2.444601 |
| RdDen | 0.0947417 | 0.0203568 | 4.65 | 0 | 0.0548336 | 0.1346499 |
| TransFq_pCap | 38.64732 | 16.57827 | 2.33 | 0.02 | 6.146737 | 71.1479 |
| _cons | 19.90315 | 3.593436 | 5.54 | 0 | 12.85846 | 26.94784 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.76 | 0.568825 | | | | |
| act_den | 1.42 | 0.701824 | | | | |
| clmalig | 1.31 | 0.762412 | | | | |
| baandabove~c | 1.24 | 0.804815 | | | | |
| TransFq_pCap | 1.23 | 0.81317 | | | | |
| RdDen | 1.16 | 0.863359 | | | | |
| perc45t064 | 1.13 | 0.88402 | | | | |
| totpop | 1.13 | 0.884319 | | | | |
| percemployed | 1.09 | 0.913351 | | | | |
| pct30mnCTW | 1.06 | 0.942559 | | | | |
| Emp_Ent | 1.03 | 0.967456 | | | | |
| Mean VIF | 1.23 | | | | | |

Table 9. Regression Results Table for Variable Vehicle Idling Alignment (Idlalign)

| | | | | | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|------------|
| Linear regression | | | Number of obs | 5,080 | | |
| | | | F(11, 5068) | 75.56 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2052 | | |
| | | | Root MSE | 10.447 | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| idlalign | -0.1290577 | 0.4975296 | -0.26 | 0.795 | -1.104431 | 0.8463153 |
| nonautoctw_pct_10 | -29.56645 | 1.927995 | -15.34 | 0 | -33.34616 | -25.78675 |
| pct30mnCTW | -0.0904578 | 0.0109053 | -8.29 | 0 | -0.111837 | -0.0690787 |
| totpop | -0.0002532 | 0.0001642 | -1.54 | 0.123 | -0.0005752 | 0.0000687 |
| perc45t064 | -0.1785364 | 0.0279992 | -6.38 | 0 | -0.2334269 | -0.1236459 |
| percemployed | -0.119832 | 0.0377728 | -3.17 | 0.002 | -0.193883 | -0.0457809 |
| baandaboveperc | 0.1435927 | 0.0073537 | 19.53 | 0 | 0.1291762 | 0.1580091 |
| act_den | 0.051562 | 0.013992 | 3.69 | 0 | 0.0241315 | 0.0789924 |
| Emp_Ent | 0.6985556 | 0.630777 | 1.11 | 0.268 | -0.53804 | 1.935151 |
| RdDen | 0.1203281 | 0.0209918 | 5.73 | 0 | 0.079175 | 0.1614811 |
| TransFq_pCap | 37.1598 | 17.45013 | 2.13 | 0.033 | 2.949998 | 71.36961 |
| _cons | 15.25045 | 3.668225 | 4.16 | 0 | 8.059144 | 22.44176 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.63 | 0.613589 | | | | |
| act_den | 1.43 | 0.701706 | | | | |
| TransFq_pCap | 1.23 | 0.813279 | | | | |
| baandabove~c | 1.17 | 0.85382 | | | | |
| RdDen | 1.16 | 0.865661 | | | | |
| totpop | 1.13 | 0.88173 | | | | |
| perc45t064 | 1.13 | 0.888136 | | | | |
| percemployed | 1.1 | 0.911531 | | | | |
| pct30mnCTW | 1.08 | 0.924979 | | | | |
| idlalign | 1.07 | 0.930678 | | | | |
| Emp_Ent | 1.03 | 0.968672 | | | | |
| Mean VIF | 1.2 | | | | | |

Table 10. Regression Results Table for Variable Goods Movement Alignment (Goodsalig)

| | | | | | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|------------|
| Linear regression | | | Number of obs | 5,080 | | |
| | | | F(11, 5068) | 89.87 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2386 | | |
| | | | Root MSE | 10.225 | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| goodsalig | -4.527502 | 0.3151414 | -14.37 | 0 | -5.145315 | -3.909688 |
| nonautoctw_pct_10 | -31.95565 | 2.030222 | -15.74 | 0 | -35.93577 | -27.97554 |
| pct30mnCTW | -0.1169899 | 0.0111364 | -10.51 | 0 | -0.1388222 | -0.0951577 |
| totpop | -0.0004667 | 0.0001759 | -2.65 | 0.008 | -0.0008117 | -0.0001218 |
| perc45t064 | -0.1945938 | 0.0273928 | -7.1 | 0 | -0.2482954 | -0.1408921 |
| percemployed | -0.1640042 | 0.0379251 | -4.32 | 0 | -0.2383539 | -0.0896546 |
| baandaboveperc | 0.1275673 | 0.0070999 | 17.97 | 0 | 0.1136485 | 0.1414861 |
| act_den | 0.0543196 | 0.0148342 | 3.66 | 0 | 0.0252382 | 0.083401 |
| Emp_Ent | 0.9338296 | 0.6216792 | 1.5 | 0.133 | -0.2849302 | 2.15259 |
| RdDen | 0.1189051 | 0.0207023 | 5.74 | 0 | 0.0783196 | 0.1594907 |
| TransFq_pCap | 38.59439 | 16.98573 | 2.27 | 0.023 | 5.29503 | 71.89376 |
| _cons | 24.72399 | 3.718759 | 6.65 | 0 | 17.43362 | 32.01437 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.67 | 0.598233 | | | | |
| act_den | 1.43 | 0.700011 | | | | |
| TransFq_pCap | 1.23 | 0.813107 | | | | |
| baandabove~c | 1.18 | 0.844879 | | | | |
| RdDen | 1.15 | 0.86793 | | | | |
| totpop | 1.14 | 0.878105 | | | | |
| perc45t064 | 1.13 | 0.885892 | | | | |
| goodsalig | 1.11 | 0.898426 | | | | |
| percemployed | 1.1 | 0.91001 | | | | |
| pct30mnCTW | 1.08 | 0.923152 | | | | |
| Emp_Ent | 1.03 | 0.968914 | | | | |
| Mean VIF | 1.21 | | | | | |

Land-use Policies

Table 11. Regression Results Table for Variable TOD Alignment (Todalig)

| Linear regression | | | Number of obs | 5,080 | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|------------|
| | | | F(11, 5068) | 76.12 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2052 | | |
| | | | Root MSE | 10.447 | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| todalig | 0.1592973 | 0.4902132 | 0.32 | 0.745 | -0.8017323 | 1.120327 |
| nonautoctw_pct_10 | -29.57197 | 1.928193 | -15.34 | 0 | -33.35207 | -25.79188 |
| pct30mnCTW | -0.0901809 | 0.0111339 | -8.1 | 0 | -0.1120082 | -0.0683536 |
| tot pop | -0.000251 | 0.0001653 | -1.52 | 0.129 | -0.0005751 | 0.0000731 |
| perc45t064 | -0.1784806 | 0.0280051 | -6.37 | 0 | -0.2333827 | -0.1235785 |
| percemployed | -0.1198651 | 0.0376719 | -3.18 | 0.001 | -0.1937183 | -0.046012 |
| baandaboveperc | 0.143441 | 0.0074574 | 19.23 | 0 | 0.1288214 | 0.1580607 |
| act_den | 0.0515605 | 0.0139896 | 3.69 | 0 | 0.0241349 | 0.0789862 |
| Emp_Ent | 0.7019599 | 0.6315159 | 1.11 | 0.266 | -0.5360842 | 1.940004 |
| RdDen | 0.1205102 | 0.0209585 | 5.75 | 0 | 0.0794225 | 0.1615979 |
| TransFq_pCap | 37.14785 | 17.44852 | 2.13 | 0.033 | 2.941205 | 71.35449 |
| _cons | 15.0775 | 3.75453 | 4.02 | 0 | 7.717002 | 22.438 |
| . vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.63 | 0.612732 | | | | |
| act den | 1.42 | 0.701775 | | | | |
| TransFq_pCap | 1.23 | 0.813222 | | | | |
| baandabove~c | 1.2 | 0.833688 | | | | |
| RdDen | 1.15 | 0.867958 | | | | |
| todalig | 1.15 | 0.868329 | | | | |
| totpop | 1.14 | 0.875127 | | | | |
| perc45t064 | 1.13 | 0.888304 | | | | |
| pct30mnCTW | 1.12 | 0.893839 | | | | |
| percemployed | 1.09 | 0.914549 | | | | |
| Emp_Ent | 1.03 | 0.967322 | | | | |
| Mean VIF | 1.21 | | | | | |

Table 12. Regression Results Table for Variable Infill Development Alignment (Infillalig)

| Linear regression | | Number of obs | 5,080 | | | |
|-------------------|-------------|-------------------|--------|-------|----------------------|------------|
| | | F(11, 5068) | 76.4 | | | |
| | | Prob > F | 0 | | | |
| | | R-squared | 0.2054 | | | |
| | | Root MSE | 10.447 | | | |
| nonautopct_cge~19 | Coefficient | Robust std . err. | t | P> t | [95% conf. interval] | |
| infillalig | 0.57104 | 0.4281802 | 1.33 | 0.182 | -0.2683782 | 1.410458 |
| nonautoctw_pct_10 | -29.61936 | 1.927889 | -15.36 | 0 | -33.39886 | -25.83987 |
| pct30mnCTW | -0.0887698 | 0.01098 | -8.68 | 0 | -0.1102954 | -0.0672441 |
| totpop | -0.0002384 | 0.000165 | -1.44 | 0.149 | -0.000562 | 0.0000851 |
| perc45t064 | -0.1783787 | 0.0280004 | -6.37 | 0 | -0.2332716 | -0.1234857 |
| percemployed | -0.1186193 | 0.037641 | -3.15 | 0.002 | -0.1924119 | 0.0448267 |
| baandaboveperc | 0.1426615 | 0.0074102 | 19.25 | 0 | 0.1281344 | 0.1571886 |
| act den | 0.0515611 | 0.0139886 | 3.69 | 0 | 0.0241374 | 0.0789848 |
| Emp_Ent | 0.7211961 | 0.631433 | 1.14 | 0.253 | -0.5166855 | 1.959078 |
| RdDen | 0.1204487 | 0.0209553 | 5.75 | 0 | 0.0793672 | 0.1615303 |
| TransFq_pCap | 37.07545 | 17.43606 | 2.13 | 0.634 | 2.893226 | 71.25767 |
| _cons | 14.51082 | 3.72312 | 3.9 | 0 | 7.211894 | 21.80974 |
| . vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.63 | 0.61168 | | | | |
| act den | 1.42 | 0.701828 | | | | |
| TransFq_pCap | 1.23 | 0.81312 | | | | |
| baandabove~c | 1.19 | 0.840668 | | | | |
| RdDen | 1.15 | 0.867951 | | | | |
| totpop | 1.14 | 0.874151 | | | | |
| infillalig | 1.13 | 0.884114 | | | | |
| perc45t064 | 1.13 | 0.888278 | | | | |
| pct30mnCTW | 1.1 | 0.908469 | | | | |
| percemployed | 1.09 | 0.914944 | | | | |
| Emp_Ent | 1.03 | 0.967465 | | | | |
| Mean VIF | 1.21 | | | | | |

Table 13. Regression Results Table for Variable Preserve Open Space Alignment (Openspacealig)

| | | | | | | |
|-------------------|-------------|------------------|---------------|--------|-----------------------|------------|
| Linear regression | | | Number of obs | 5,080 | | |
| | | | F(11, 5068) | 77.13 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2103 | | |
| | | | Root MSE | 10.414 | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| openspacealig | 2.093037 | 0.2963346 | 7.06 | 0 | 1.512093 | 2.673981 |
| nonautoctw_pct_10 | -30.54421 | 1.91771 | -15.93 | 0 | -34.30375 | -26.78467 |
| pct30mnCTW | -0.0840668 | 0.0106091 | -7.92 | 0 | -0.1048652 | -0.0632683 |
| totpop | -0.0001122 | 0.0001628 | -0.69 | 0.491 | -0.0004314 | 0.0002069 |
| perc45t064 | -0.1753459 | 0.0278158 | -6.3 | 0 | -0.2298768 | -0.120815 |
| percemployed | -0.10576 | 0.0377541 | -2.8 | 0.005 | -0.1797742 | -0.0317457 |
| baandaboveperc | 0.1420512 | 0.0072384 | 19.62 | 0 | 0.1278609 | 0.1562416 |
| act den | 0.0509292 | 0.0138842 | 3.67 | 0 | 0.0237101 | 0.0781484 |
| Emp_Ent | 0.6733689 | 0.628267 | 1.07 | 0.284 | -0.558306 | 1.905044 |
| RdDen | 0.1198785 | 0.0208383 | 5.75 | 0 | 0.0790264 | 0.1607307 |
| TransFq_pCap | 35.76593 | 16.94051 | 2.11 | 0.035 | 2.555204 | 68.97666 |
| _cons | 11.98805 | 3.681868 | 3.26 | 0.001 | 4.769995 | 19.2061 |
| . vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.68 | 0.596468 | | | | |
| act den | 1.43 | 0.70122 | | | | |
| TransFq_pCap | 1.23 | 0.812199 | | | | |
| totpop | 1.16 | 0.864942 | | | | |
| baandabovevc | 1.15 | 0.867329 | | | | |
| RdDen | 1.15 | 0.86793 | | | | |
| openspacealig | 1.14 | 0.879808 | | | | |
| perc45t064 | 1.13 | 0.8877 | | | | |
| percemployed | 1.1 | 0.912176 | | | | |
| pct30mnCTW | 1.06 | 0.939761 | | | | |
| Emp_Ent | 1.83 | 0.969566 | | | | |
| Mean VIF | 1.2 | | | | | |

Table 14. Regression Results Table for Variable ADU Development Alignment (Adualign)

| Linear regression | | Number of obs | 5,080 | | | |
|-------------------|-------------|------------------|--------|-------|----------------------|------------|
| | | F(11, 5068) | 87.65 | | | |
| | | Prob > F | 0 | | | |
| | | R-squared | 0.2368 | | | |
| | | Root MSE | 10.238 | | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| adualig | -4.366051 | 0.3197052 | -13.66 | 0 | -4.992811 | -3.73929 |
| nonautoctw_pct_10 | -31.46691 | 2.057642 | -15.29 | 0 | -35.50078 | -27.43304 |
| pct30mnCTW | -0.1260673 | 0.0113105 | -11.15 | 0 | -0.1482407 | -0.103894 |
| tot pop | -0.0004185 | 0.0001733 | -2.41 | 0.016 | -0.0007583 | -0.0000788 |
| perc45t064 | -0.1846274 | 0.0276461 | -6.68 | 0 | -0.2388257 | -0.1304292 |
| percemployed | -0.1459229 | 0.0379142 | -3.85 | 0 | -0.2202512 | -0.0715947 |
| baandaboveperc | 0.1356733 | 0.0070974 | 19.12 | 0 | 0.1217593 | 0.1495873 |
| act den | 0.0551422 | 0.0151695 | 3.64 | 0 | 0.0254034 | 0.0848809 |
| Emp_Ent | 1.011932 | 0.6242207 | 1.62 | 0.105 | -0.2118103 | 2.235675 |
| RdDen | 0.1340854 | 0.0208092 | 6.44 | 0 | 0.0932904 | 0.1748803 |
| TransFq_pCap | 38.37241 | 17.61666 | 2.18 | 0.029 | 3.836143 | 72.90868 |
| _cons | 21.83555 | 3.67426 | 5.94 | 0 | 14.63241 | 29.03868 |
| . vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.66 | 0.603426 | | | | |
| act den | 1.43 | 0.698599 | | | | |
| TransFq_pCap | 1.23 | 0.813149 | | | | |
| baandabove~c | 1.16 | 0.862618 | | | | |
| RdDen | 1.16 | 0.865666 | | | | |
| totpop | 1.14 | 0.880577 | | | | |
| perc45t064 | 1.13 | 0.887933 | | | | |
| pct30mnCTW | 1.11 | 0.897529 | | | | |
| adualig | 1.09 | 0.915199 | | | | |
| percemployed | 1.09 | 0.915215 | | | | |
| Emp_Ent | 1.63 | 0.968319 | | | | |
| Mean VIF | | 1.2 | | | | |

Table 15. Regression Results Table for Variable Housing Near Activity Centers Alignment (Hncalig)

| Linear regression | | Number of obs | | 5,080 | | |
|-------------------|-------------|------------------|--------|--------|----------------------|------------|
| | | F(11, 5068) | | 75.63 | | |
| | | Prob > F | | 0 | | |
| | | R-squared | | 0.2053 | | |
| | | Root MSE | | 10.447 | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| hncalig | 0.4021737 | 0.4109842 | 0.98 | 0.328 | -0.4035328 | 1.20788 |
| nonautoctw_pct_10 | -29.6016 | 1.920534 | -15.41 | 0 | -33.36668 | -25.83653 |
| pct30mnCTW | -0.0894228 | 0.0109466 | -8.17 | 0 | -0.1108828 | -0.0679627 |
| totpop | -0.0002458 | 0.0001654 | -1.49 | 0.137 | -0.0005701 | 0.0000786 |
| perc45t064 | 0.1782873 | 0.0280158 | -6.36 | 0 | -0.2332104 | -0.1233643 |
| percemployed | 0.1196545 | 0.0376121 | -3.18 | 0.001 | -0.1933904 | -0.0459186 |
| baandaboveperc | 0.1433398 | 0.0073254 | 19.57 | 0 | 0.1289788 | 0.1577008 |
| act den | 0.0514673 | 0.0139806 | 3.68 | 0 | 0.0240592 | 0.0788754 |
| Emp_Ent | 0.710453 | 0.6309938 | 1.13 | 0.26 | -0.5265677 | 1.947474 |
| RdDen | 0.1194376 | 0.0210111 | 5.68 | 0 | 0.0782468 | 0.1606283 |
| TransFq_pCap | 37.24335 | 17.48229 | 2.13 | 0.033 | 2.970505 | 71.51619 |
| _cons | 14.81915 | 3.701372 | 40 | 0 | 7.562857 | 22.07544 |
| . vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.63 | 0.612037 | | | | |
| act den | 1.43 | 0.701036 | | | | |
| TransFq_pCap | 1.23 | 0.813019 | | | | |
| baandabove~c | 1.16 | 0.861764 | | | | |
| RdDen | 1.16 | 0.861879 | | | | |
| totpop | 1.14 | 0.878955 | | | | |
| perc45t064 | 1.13 | 0.888141 | | | | |
| hncalig | 1.1 | 0.910518 | | | | |
| pct30mnCTW | 1.09 | 0.916916 | | | | |
| percemployed | 1.09 | 0.917314 | | | | |
| Emp_Ent | 1.03 | 0.968296 | | | | |
| Mean VIF | 1.2 | | | | | |

Table 16. Regression Results Table for Variable Parking Requirements Alignment (Parkingalig)

| Linear regression | | Number of obs | 5,080 | | | |
|-------------------|-------------|------------------|--------|--------|----------------------|------------|
| | | F(11, 5068) | 77.17 | | | |
| | | Prob > F | 0 | | | |
| | | R- squared | 0.2081 | | | |
| | | Root MSE | 10.428 | | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| parkingalig | 1.599253 | 0.3106089 | 5.15 | 0 | 0.9903256 | 2.208181 |
| nonautoctw_pct_10 | -30.32739 | 1.88038 | -16.13 | 0 | -34.01375 | -26.64103 |
| pct30mnCTW | -0.0761592 | 0.0112822 | -6.75 | 0 | -0.0982773 | -0.0540411 |
| totpop | -0.001882 | 0.0001647 | -1.14 | 0.0253 | -0.0005111 | . e001347 |
| perc45t064 | -0.1776128 | 0.027959 | -6.35 | 0 | -0.2324245 | -0.1228011 |
| percemployed | -0.1212044 | 0.0374623 | -3.24 | 0.0001 | -0.1946466 | -0.0477622 |
| baandaboveperc | 0.142802 | 0.0072704 | 19.64 | 0 | 0.128549 | 0.157055 |
| act den | 0.0504619 | 0.0137802 | 3.66 | 0 | 0.0234467 | 0.077477 |
| Emp_Ent | 0.7011392 | 0.6285639 | 1.12 | 0.0265 | -0.5311176 | 1.933396 |
| RdDen | 0.116057 | 0.0208049 | 5.58 | 0 | 0.0752705 | 0.1568435 |
| TransFq_pCap | 36.76282 | 17.36988 | 2.12 | 0.0034 | 2.710353 | 70.81528 |
| _cons | 13.68303 | 3.636619 | 3.76 | 0 | 6.553682 | 20.81237 |
| . vif Variable | VIF | 1/VIF | | | | |
| nonautoctæ10 | 1.68 | 0.595306 | | | | |
| act den | 1.43 | 0.698558 | | | | |
| parkingalig | 1.27 | 0.786318 | | | | |
| TransFq_pCap | 1.23 | 0.813125 | | | | |
| pct30mnCTW | 1.17 | 0.853891 | | | | |
| RdDen | 1.16 | 0.865265 | | | | |
| baandabove~c | 1.15 | 0.868149 | | | | |
| totpop | 1.14 | 0.877083 | | | | |
| perc45t064 | 1.13 | 0.888223 | | | | |
| percemployed | 1.09 | 0.91817 | | | | |
| Emp_Ent | 1.03 | 0.969599 | | | | |
| Mean VIF | 1.23 | | | | | |

Table 17. Regression Results Table for Variable Urban Forest Alignment (Ufalign)

| Linear regression | | Number of obs | 5,080 | | | |
|-------------------|-------------|-------------------|----------|-------|----------------------|------------|
| | | F(11, 5068) | 88.99 | | | |
| | | Prob > F | 0 | | | |
| | | R-squared | 0.2393 | | | |
| | | Root MSE | 10.221 | | | |
| nonautopct_cge~19 | Coefficient | Robust std . err. | t | P> t | [95% conf. interval] | |
| ufalign | -4.517554 | 0.314718 | -14.35 | 0 | -5.134537 | -3.90057 |
| nonautoctw_pct_10 | -31.66274 | 2.038804 | -15.53 | 0 | -35.65967 | -27.6658 |
| pct30mnCTW | -0.1231275 | 0.011341 | -10.86 | 0 | -0.1453608 | -0.1008942 |
| totpop | -0.0004416 | 0.0001727 | -2.56 | 0.011 | -0.00078 | -0.0001031 |
| perc45t064 | -0.1887054 | 0.0274314 | -6.88 | 0 | -0.2424828 | -0.134928 |
| percemployed | -0.1480655 | 0.0379442 | -3.9 | 0 | -0.2224525 | -0.0736785 |
| baandaboveperc | 0.1313466 | 0.0070822 | 18.55 | 0 | 0.1174624 | 0.1452308 |
| act den | 0.0545345 | 0.0149623 | 3.64 | 0 | 0.0252019 | 0.0838672 |
| Emp_Ent | 0.9562432 | 0.6232386 | 1.53 | 0.125 | -0.2655738 | 2.17806 |
| RdDen | 0.1260975 | 0.0207091 | 6.09 | 0 | 0.0854987 | 0.1666964 |
| TransFq_pCap | 38.55115 | 17.08346 | 2.26 | 0.024 | 5.660175 | 72.04212 |
| _cons | 22.78777 | 3.687645 | 6.18 | 0 | 15.55839 | 30.01715 |
| . vif Variable | VIF | I/VIF | | | | |
| nonautoct~10 | | 1.66 | 0.602079 | | | |
| act den | | 1.43 | 0.699761 | | | |
| TransFq_pCap | | 1.23 | 0.81312 | | | |
| baandaboveæc | | 1.17 | 0.855006 | | | |
| baandabove~c | | 1.15 | 0.867599 | | | |
| totpop | | 1.14 | 0.879704 | | | |
| perc45t064 | | 1.13 | 0.887351 | | | |
| pct30mnCTW | | 1.1 | 0.9092 | | | |
| percemployed | | 1.09 | 0.914951 | | | |
| ufalign | | 1.09 | 0.915408 | | | |
| Emp_Ent | | 1.03 | 0.968794 | | | |
| Mean VIF | | 1.2 | | | | |

Transportation Demand Management (TDM) Strategies

Table 18. Regression Results Table for Variable TDM Alignment (Tdmalig)

| Linear regression | | | Number of obs | 5,080 | | |
|-------------------|-------------|-------------------|---------------|--------|----------------------|------------|
| | | | F(11, 5068) | 77.22 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2097 | | |
| | | | Root MSE | 10.418 | | |
| nonautopct_cge~19 | Coefficient | Robust std . err. | t | P> t | [95% conf. interval] | |
| tdmalig | 2.33462 | 0.323362 | 7.22 | 0 | 1.70069 | 2.968549 |
| nonautoctw_pct_10 | -30.3536 | 1.942027 | -15.63 | 0 | -34.16081 | -26.54638 |
| pct30mnCTW | -0.0827392 | 0.0106984 | -7.73 | 0 | -0.1037128 | -0.0617657 |
| totpop | -0.0001123 | 0.0001638 | -0.69 | 0.493 | -0.0004334 | 0.0002087 |
| perc45t064 | -0.1737877 | 0.0279541 | -6.22 | 0 | -0.2285898 | -0.1189856 |
| percemployed | -0.1049842 | 0.0377546 | -2.78 | 0.005 | -0.1789995 | -0.030969 |
| baandaboveperc | 0.1433438 | 0.0072595 | 19.75 | 0 | 0.129112 | 0.1575755 |
| act den | 0.0515496 | 0.0140501 | 3.67 | 0 | 0.0240053 | 0.079094 |
| Emp_Ent | 0.7195473 | 0.628405 | 1.15 | 0.252 | -0.5123981 | 1.951493 |
| RdDen | 0.12617 | 0.020988 | 6.01 | 0 | 0.0850243 | 0.1673156 |
| TransFq_pCap | 36.05489 | 17.25307 | 2.09 | 0.037 | 2.231418 | 69.87837 |
| _cons | 11.11248 | 3.725731 | 2.98 | 0.003 | 3.808439 | 18.41652 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | | 1.66 | 0.601042 | | | |
| act den | | 1.42 | 0.701832 | | | |
| TransFq_pCap | | 1.23 | 0.812509 | | | |
| totpop | | 1.16 | 0.86237 | | | |
| RdDen | | 1.16 | 0.865135 | | | |
| baandabove~c | | 1.15 | 0.869028 | | | |
| perc45t064 | | 1.13 | 0.886769 | | | |
| tdmalig | | 1.11 | 0.899466 | | | |
| percemployed | | 1.1 | 0.910632 | | | |
| pct30mnCTW | | 1.07 | 0.931751 | | | |
| Emp_Ent | | 1.03 | 0.96955 | | | |
| Mean VIF | | 1.2 | | | | |

Cross-cutting Issues

Table 19. Regression Results Table for Variable Regional Collaboration Alignment
(Regcollabalig)

| Linear regression | | Number of obs | 5,080 | | | |
|-------------------|-------------|------------------|--------|-------|----------------------|------------|
| | | F(11, 5068) | 76.04 | | | |
| | | Prob > F | 0 | | | |
| | | R-squared | 0.2061 | | | |
| | | Root MSE | 10.442 | | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| regcollabalig | -0.9302787 | 0.4128248 | -2.25 | 0.024 | -1.739594 | -0.1209638 |
| nonautoctw_pct_10 | -29.41891 | 1.931052 | -15.23 | 0 | -33.20461 | -25.63322 |
| pct30mnCTW | -0.0914022 | 0.0107434 | -8.51 | 0 | -0.112464 | -0.0703405 |
| tot pop | -0.0002805 | 0.0001664 | -1.69 | 0.092 | -0.0006066 | 0.0000457 |
| perc45t064 | -0.1795254 | 0.027959 | -6.42 | 0 | -0.2343371 | -0.1247137 |
| percemployed | -0.1224209 | 0.0376835 | -3.25 | 0.001 | -0.1962969 | -0.0485449 |
| baandaboveperc | 0.1425279 | 0.0073122 | 19.49 | 0 | 0.1281929 | 0.1568629 |
| act den | 0.0520324 | 0.0140905 | 3.69 | 0 | 0.0244088 | 0.079656 |
| Emp_Ent | 0.7683569 | 0.6319076 | 1.22 | 0.224 | -0.4704551 | 2.007169 |
| RdDen | 0.1184083 | 0.0210733 | 5.62 | 0 | 0.0770955 | 0.1597212 |
| TransFq_pCap | 36.86168 | 17.39116 | 2.12 | 0.034 | 2.767482 | 70.95588 |
| _cons | 16.38018 | 3.71678 | 4.41 | 0 | 9.093681 | 23.66667 |
| . vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.63 | 0.612098 | | | | |
| act den | 1.43 | 0.699773 | | | | |
| TransFq_pCap | 1.23 | 0.812996 | | | | |
| baandabove~c | 1.16 | 0.863792 | | | | |
| RdDen | 1.15 | 0.866015 | | | | |
| totpop | 1.13 | 0.88116 | | | | |
| perc45t064 | 1.13 | 0.887923 | | | | |
| percemployed | 1.09 | 0.917494 | | | | |
| pct30mnCTW | 1.05 | 0.952169 | | | | |
| Emp_Ent | 1.03 | 0.967159 | | | | |
| regcollabalig | 1.03 | 0.975464 | | | | |
| Mean VIF | 1.19 | | | | | |

Table 20. Regression Results Table for Variable Community Involvement and Outreach Alignment (Cioalig)

| Linear regression | | | Number of obs | 5,080 | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|------------|
| | | | F(11, 5068) | 96.52 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.247 | | |
| | | | Root MSE | 10.169 | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| cioalig | -5.497138 | 0.34799 | -15.8 | 0 | -6.179349 | -4.814927 |
| nonautoctw_pct_10 | -32.91264 | 1.985654 | -16.58 | 0 | -36.80538 | -29.6199 |
| pct30mnCTW | 0.0811447 | 0.010619 | -7.64 | 0 | 0.1019625 | -0.0603269 |
| totpop | -0.0004743 | 0.0001722 | -2.75 | 0.006 | -0.0008119 | -0.0001367 |
| perc45t064 | -0.2003269 | 0.0272376 | -7.35 | 0 | -0.2537244 | -0.1469293 |
| percemployed | -0.1680691 | 0.0376765 | -4.46 | 0 | -0.2419313 | -0.0942069 |
| baandaboveperc | 0.1177426 | 0.00713 | 16.51 | 0 | 0.1037646 | 0.1317205 |
| act den | 0.0527874 | 0.0144348 | 3.66 | 0 | 0.0244889 | 0.0810859 |
| Emp_Ent | 1.210564 | 0.619529 | 1.95 | 0.051 | -0.0039804 | 2.425109 |
| RdDen | 0.1093709 | 0.0204603 | 5.35 | 0 | 0.0692598 | 0.149482 |
| TransFq_pCap | 38.75727 | 16.92862 | 2.29 | 0.022 | 5.569862 | 71.94468 |
| _cons | 25.34215 | 3.683468 | 6.88 | 0 | 18.12096 | 32.56334 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoctælø | 1.7 | 0.5895 | | | | |
| act den | 1.43 | 0.701541 | | | | |
| TransFq_pCap | 1.23 | 0.813108 | | | | |
| baandabove~c | 1.22 | 0.820428 | | | | |
| cioalig | 1.18 | 0.845249 | | | | |
| RdDen | 1.15 | 0.866792 | | | | |
| totpop | 1.14 | 0.879047 | | | | |
| perc45t064 | 1.13 | 0.884759 | | | | |
| percemployed | 1.1 | 0.910364 | | | | |
| pct30mnCTW | 1.85 | 0.949526 | | | | |
| Emp_Ent | 1.03 | 0.967032 | | | | |
| Mean VIF | 1.21 | | | | | |

Table 21. Regression Results Table for Variable Equity Alignment (Equalig)

| Linear regression | | | Number of obs | 5,080 | | |
|-------------------|-------------|------------------|---------------|--------|----------------------|------------|
| | | | F(11, 5068) | 75.77 | | |
| | | | Prob > F | 0 | | |
| | | | R-squared | 0.2053 | | |
| | | | Root MSE | 10.447 | | |
| nonautopct_cge~19 | Coefficient | Robust std. err. | t | P> t | [95% conf. interval] | |
| equal ig | 0.255167 | 0.3215786 | 0.79 | 0.428 | -0.3752661 | 0.8856001 |
| nonautoctw_pct_10 | -29.62787 | 1.918347 | -15.44 | 0 | -33.38866 | -25.86708 |
| pct30mnCTW | 0.0892797 | 0.0111185 | -8.03 | 0 | 0.1110768 | -0.0674826 |
| totpop | -0.0002436 | 0.000166 | -1.47 | 0.142 | -0.000569 | 0.0000818 |
| perc45t064 | -0.1785679 | 0.0280079 | -6.38 | 0 | -0.2334754 | -0.1236603 |
| percemployed | -0.1198434 | 0.0375854 | -3.19 | 0.001 | -0.193527 | -0.0461599 |
| baandaboveperc | 0.1431986 | 0.0073589 | 19.46 | 0 | 0.128772 | 0.1576253 |
| act den | 0.05148 | 0.0139823 | 3.68 | 0 | 0.0240685 | 0.0788914 |
| Emp_Ent | 0.7076301 | 0.6304516 | 1.12 | 0.262 | -0.5283274 | 1.943588 |
| RdDen | 0.1193273 | 0.0210147 | 5.68 | 0 | 0.0781294 | 0.1605252 |
| TransFq_pCap | 37.16168 | 17.44909 | 2.13 | 0.033 | 2.953916 | 71.36944 |
| cons | 15.00779 | 3.662779 | 4.1 | 0 | 7.827157 | 22.18842 |
| vif Variable | VIF | 1/VIF | | | | |
| nonautoct~10 | 1.65 | 0.606347 | | | | |
| act den | 1.43 | 0.701056 | | | | |
| TransFq_pCap | 1.23 | 0.81328 | | | | |
| equalig | 1.2 | 0.833019 | | | | |
| baandabove~c | 1.17 | 0.85151 | | | | |
| RdDen | 1.17 | 0.858056 | | | | |
| totpop | 1.15 | 0.872972 | | | | |
| perc45t064 | 1.13 | 0.888263 | | | | |
| pct30mnCTW | 1.12 | 0.895235 | | | | |
| percemployed | 1.89 | 0.917588 | | | | |
| Emp_Ent | 1.03 | 0.968432 | | | | |
| Mean VIF | 1.21 | | | | | |

Endnotes

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⁴ Allred and Arnab Chakraborty, “Do Local Development Outcomes Follow Voluntary Regional Plans? Evidence from Sacramento Region’s Blueprint Plan,” *Journal of the American Planning Association* 81, no. 2 (2015): 104–20.

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¹² “Public Participation Plan for the San Francisco Bay Area,” June 27, 2018, MTC, https://www.planbayarea.org/sites/default/files/pdfs_referenced/2018_ppp_appendix_a_final_june2018.pdf.

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