Travel Behavior and Transportation Planning Insights from the Small Urban Area of Chittenden County, Vermont: An Application of Traveler Segmentation

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Disclaimer

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Executive Summary

The primary purpose of this project is to analyze transportation planning and travel behavior in the small urban area of Chittenden County, Vermont. The 2000, 2006, 2012, and 2018 travel surveys conducted for the Chittenden County Regional Planning Commission serve as the primary data sources. This survey series was designed to collect information from the public about transportation attitudes as well as priorities for regional transportation planning investments. We use cluster analysis to segment travelers into three modal orientations – Alternative Oriented, Car Tolerant, and Car Oriented – based on eight factors:

1. Would Change Travel Behavior with Change in Conditions
2. Perceive Car as Only Option
3. Concerned with Congestion, Safety, and Environmental Impacts
4. Transit/Bike/Walk Enthusiast
5. Prioritized Highway Improvements
6. Prioritizes General Roadway Improvements
7. Prioritizes Incentives for Alternatives
8. Prioritizes Improvements for Transit, Biking, and Walking

With a focus on both modal orientations and changes over time, we analyze nine outcomes (seven behavioral and two planning) organized into three categories:

- ***Travel Indicators***
    - *Household Vehicles*
    - *Mode Use*
    - *Commuter Benefit Use*
- ***Telecommunications***
    - *Teleworking Availability*
    - *Teleworking Interest*
    - *Teleworking Use*
    - *Trip Reduction Due to the Internet*
- ***Planning Priorities***
    - *Regional Spending by Category*
    - *Support for Increasing Gas Taxes*

Our findings suggest the modal orientations represent a spectrum of automobile reliance (in terms of behavior) and support for automobile accommodation (in terms of planning). The Alternative Oriented comprises 28% of the pooled 2000-2018 sample, while the Car Tolerant comprises 49% and the Car Oriented comprises 23%. Limited resources for concentrated marketing should focus on the Car Tolerant; this modal orientation group has a high willingness to change travel behavior with a change in travel conditions and reports strong support for incentives for alternatives but also perceives the car as the only option at a relatively high rate. The Car Tolerant could be encouraged to increase the intensity with which they use alternative modes and be introduced to supportive alternatives such as electric bicycles and carsharing.

Beyond the modal orientations, our results indicate strong public support for a shift away from automobile accommodation and toward support for alternatives. The Chittenden County public would like fewer resources devoted to highways than is currently being allocated, and support for gas tax increases is higher for non-highway purposes than for use exclusive to highways. While transportation planning and travel behavior in the U.S. have historically reinforced an orientation toward the automobile, it is also possible to harness this cycle in support of alternatives modes as well. Our findings suggest there is likely to be more public support for truly balanced transportation systems than has typically been understood or expected.

	Alternative Oriented	**Car Tolerant**	**Car Oriented**	**Basis**
Travel Indicators				
Household Vehicles	0 Vehicles (Highest)	1-2 Vehicles (Highest)	3+ Vehicles (Highest)	Regression
Mode Use	Regular Transit, Bike, or Walk (Highest)	Regular Driver with Occasional Transit, Bike, or Walk (Highest)	Regular Driver Without Occasional Transit, Bike, or Walk (Highest)	Regression
Commuter Benefits	Parking Use (Lowest); Transit Use (Highest)	Parking Use (Middle); Transit Use (Middle)	Parking Use (Highest); Transit Use (Lowest)	Tabulation
Telecommunications				
Telework Availability	Even			Regression
Telework Interest	Higher (Even)		Lower	Tabulation
Telework Offer	Highest Use	Lowest Use	Middle Use	Tabulation
Trip Reductions Due to Internet	Medium	Highest	Lowest	Regression
Planning Priorities				
Spending by Category	Highway (Lowest); Transit (Highest); Bike/Walk (Highest)	Highway (Middle); Transit (Middle); Bike/Walk (Middle)	Highway (Highest); Transit (Lowest); Bike/Walk (Lowest)	Tabulation
Support for Gas Tax Increase - Highway Only	Lower (Even)	Highest	Lower (Even)	Regression
Support for Gas Tax Increase - Non-Highway	Highest	Middle	Lowest	Regression
Based on Regression Where Available (Otherwise Cross Tabulations for Pooled Samples)				

Chapter 1: Introduction

Transportation in the U.S. is characterized by a mutually reinforcing and relatively high level of automobile accommodation (from a planning perspective) and reliance (from a behavioral perspective). Scholars have emphasized that this is both unique among international peers, and a result of choices, individual and collective, rather than inevitabilities (Vuchic 1999, Giuliano and Handy 2004). These choices manifest the tension inherent in “managing the auto” as a source of both unprecedented mobility as well as multi-faceted and sometimes detrimental environmental, health, safety, financial, and equity impacts (Giuliano and Handy 2004). In many American communities, this tension has been confronted with increasing support for “balanced” transportation (Wickstrom 1971), which in practice has often been translated into continued automobile accommodation coupled with expanded (albeit limited) multimodal investments, and a high degree of reluctance toward significant restraints on the auto.

In many cases, persistent prioritization of automobile accommodations together with limited investment in alternatives result in competing or countervailing policies and programs that may generate partial gains in efficiency and equity, but also lead to the over-utilization of resources and higher overall costs (Segelhorst and Kirkus 1973, Vuchic 1999). To use resources more judiciously and realize more fully the benefits of a balanced transport system, focused attention is needed on the transportation investments (collective priorities) and travel behavior outcomes (individual choices) that result from a context of auto restraint reluctance. Indeed, achieving goals related to “the demand side of the transportation sector requires examining not only travel behavior, which has long been the focus of research, but also transportation planning and project prioritization” (Mullin, Feiock et al. 2020, who emphasize the goal of climate change mitigation).

The primary purpose of this project is to analyze transportation planning and behavioral outcomes in the small urban area of Chittenden County, Vermont, with a focus on automobile accommodation and reliance in relation to more sustainable alternatives. The analysis includes evaluation of nine outcomes (seven behavioral and two planning) organized around three categories:

- ***Travel Indicators***
    - *Household Vehicles*
    - *Mode Use*
    - *Commuter Benefit Use*
- ***Telecommunications***
    - *Teleworking Availability*
    - *Teleworking Interest*
    - *Teleworking Use*
    - *Trip Reduction Due to the Internet*
- ***Planning Priorities***
    - *Regional Spending by Category*
    - *Support for Increasing Gas Taxes*

This project makes several unique contributions. To our knowledge, this is the first study in the sustainable transportation literature to employ traveler segmentation in a small urban area. In addition, it is the first comprehensive scholarly treatment of a unique travel survey series collected for Chittenden County in 2000, 2006, 2012, and 2018. Finally, to our knowledge, it offers the first direct comparison of a small urban MPO's transportation spending in relation to the spending priorities of the public which it serves. With this project, we hope to contribute to a greater understanding of transportation planning and travel behavior in the small urban context as well as provide insights that may support the realization of a more balanced transport system.

Chapter 2: Empirical Approach

Co-Authors: Andrea Hamre & Jonathan Fisher

This chapter provides an overview of this project's empirical approach. It is divided into six sections: study area; overview of the data; preparation of the data; generation of survey weights; factor identification and cluster segmentation; and models and hypotheses.

Study Area

The study area (**Figure 1**) for this project comprises Chittenden County ("CC"), Vermont, which shares a coterminous boundary with the state's only Metropolitan Planning Organization ("MPO"), the Chittenden County Regional Planning Commission ("CCRPC"). CC has an estimated population of 163,773, containing about a quarter of Vermont's 626,299 estimated residents (U.S. Census Bureau 2019). Major regional roadways include Interstate 89, as well as US Routes 2 (east-west) and 7 (north-south). The region is served by Green Mountain Transit (previously Chittenden County Transportation Authority) as well as a network of Park-and-Ride locations. Several paved paths, including the Island Line Trail along Lake Champlain, support biking and walking in the region.

The largest city in CC, Burlington, is also the state's largest; with an estimated population of 42,819, Burlington contains about a fourth of the CC population (U.S. Census Bureau 2019). Burlington sits on the eastern shore of Lake Champlain, across from New York State, and serves as a hub of activity for the regional and state populations, including home to the University of Vermont. Compared to the regional population as a whole, Burlington is denser (4,116 population per square mile versus 292), has fewer commuters relying on driving alone (53% versus 73%), and has a lower median household income ($50,324 versus $69,896) (U.S. Census Bureau 2019a, U.S. Census Bureau 2019b). From a transportation perspective, Burlington is relatively unique for CC and the state, in the degree to which alternatives to driving are available. Along with the Green Mountain Transit (formerly Chittenden County Transportation Authority) service, CarShare Vermont has offered carsharing to the public since 2008 and a public bikesharing system was introduced in 2018.

CCRPC has demonstrated the support for "balanced" transportation discussed above, as evidenced by a commitment to multimodal transportation investments. The 1976 regional plan argues that "planning for the various modes of transportation…should be integrated in an economically beneficial manner" and that, "by means of an integrated transportation system we desire to enhance the viability of our Region by making commercial, industrial and institutional areas more accessible to all modes of transportation, particularly public transportation" (Chittenden County Regional Planning Commission 1976). The 1996 regional plan describes the goal to "integrate public transportation considerations in land use planning" and "establish a regional, multi-purpose greenway system of bicycle and pedestrian paths" (Chittenden County Regional Planning Commission 1996). The 2013 regional plan (as amended May 2016) stressed the need for "more robust investment in transportation options" in order to "reduce congestion, vehicle miles traveled, use of single occupancy vehicles," and more, with an increased emphasis on combating climate change (Chittenden County Regional Planning Commission 2016). The

2018 regional plan declares that "it is imperative that we continue to support efforts to reduce VMT per capita and single-occupancy vehicle (SOV) travel", describes the goal to "provide accessible, safe, efficient, interconnected, secure, equitable and sustainable mobility choices for our region's businesses, residents and visitors", and emphasizes that "directing transportation investments to service mobility and accessibility in compact settlements will result in a more cost-effective and efficient transportation system" (Chittenden County Regional Planning Commission 2018). However, as is common for transportation planning in the U.S., significant investments to accommodate automobile travel continue in the region as well. Over the past several decades, a number of regionally significant roadway projects have received attention (but also faced considerable and in some cases insurmountable levels of opposition and legal challenges), including the Chittenden County Circumferential Highway (ultimately abandoned due to legal and environmental challenges) and the Burlington Belt Line (with its Southern Connector, renamed the Champlain Parkway). As summarized in Table 7 in the 2018 plan, projects oriented toward accommodation of automobile travel comprised the bulk of funding (e.g., 17.3% for paving, 21.5% for bridges, and 21.9% for new facility/major roadway upgrades respectively) included in the region's Transportation Improvement Programs between FY2000 and 2016 (Chittenden County Regional Planning Commission 2018). See further analysis of regional spending by category in Chapter 5.

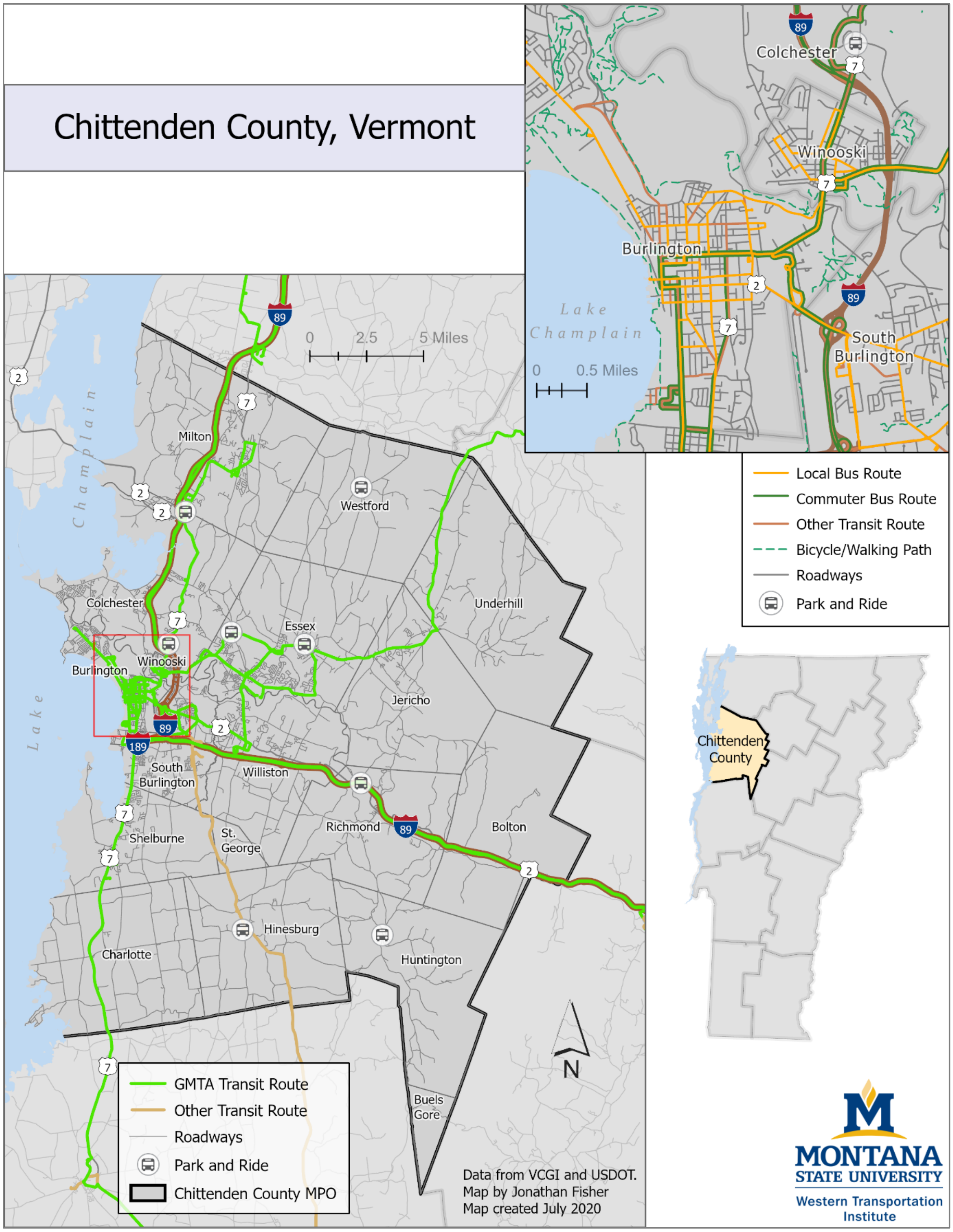

Figure 1 Map of the Study Area

Note: Map created using geospatial data from the Vermont Center for Geographic Information and the Bureau of Transportation Statistics Open Data Catalog. Transit routes reflect current Green Mountain Transit system.

Overview of the Data

The primary data sources for this project are the 2000, 2006, 2012, and 2018 travel surveys conducted for CCRPC (Chittenden County Regional Planning Commission 2001, Chittenden County Regional Planning Commission 2006, Chittenden County Regional Planning Commission 2012, Chittenden County Regional Planning Commission 2018). This survey series was designed to collect information from the public about transportation attitudes as well as priorities for regional transportation planning investments. In addition, the surveys collected a limited set of sociodemographic and travel behavior measures.[1] In contrast to the household travel surveys typically collected for travel demand modeling, this survey series did not include a full accounting of tripmaking (such as would be available through trip diaries). **Table 1** summarizes several key characteristics of the survey series. While the primary purpose and many of the survey questions remained consistent across the series, several important adjustments were made with respect to the survey designs and instruments:

- The 2000 and 2006 surveys targeted CC residents as well as employees (who did not necessarily reside within the county), while the 2012 and 2018 surveys only targeted CC residents.
- The 2000 survey of residents was based on intercept surveys at multiple sites around the county, generating a non-probabilistic sample. In contrast, the 2006, 2012, and 2018 survey of residents utilized address-based random sampling, generating probabilistic samples.
- The 2000 and 2006 surveys of employees utilized lists of CC businesses, generating non-probabilistic samples.
- The 2000 and 2006 surveys of CC residents used paper collection, while the surveys of CC employees used online collection. In 2012, CC residents were provided paper and online option. In 2018, all surveys were collected online.
- The 2000 survey was conducted in the fall season, while the 2006, 2012, and 2018 surveys were conducted in the spring season. Exact dates for the survey deployment could not be ascertained from available information.
- The scales for questions regarding both transportation attitudes and planning project priorities changed after 2000. All four surveys used 5-point scales, but the 2000 survey placed neutral (attitudinal) and no opinion (priorities) response in position 3 (the middle of the scale) while the remaining three surveys replaced these with a don’t know option in position 5 (the top end of the scale).
- The 2000 survey included two options below the neutral position for the priority questions (not at all important, not important) while the remaining three surveys included only one comparable option (not at all important). The two options available in 2000 above the neutral position (important, very important) had three comparable options in the other three surveys (somewhat important, very important, essential).
- Income was collected in six categories in 2000 that did not align well with U.S. Census data collection, while the remaining three surveys collected income with nine categories well-aligned with the Census.

[1] Notably, race/ethnicity was not collected in any of the surveys.

- The 2000, 2006, and 2018 surveys collected residential zip code, while that information was missing from the 2012 survey. The 2012 and 2018 surveys included an option to self-report the geographic residential setting based on six categories.
- Educational attainment was not collected in 2000.
- The main mode used for most trips, other modes used over the course of the month, and commuter benefits (with regard to telecommuting, flex time, compressed work schedule, car parking, transit, and carpooling) were only collected in 2012 and 2018.
- The assessment of relative weight given to the planning priorities changed over time. The 2000 survey used randomized pairings, while the 2006 and 2012 surveys collected rankings, and the 2018 survey asked respondents to distribute points.

Table 1 Summary of the Chittenden County Travel Surveys by Year

	2000	**2006**	**2012**	**2018**
Sample Target	Chittenden County Residents & Employees	Chittenden County Residents & Employees	Chittenden County Residents	Chittenden County Residents
Sampling Method	Residents: Non-Random (Multi-Site Intercepts) Employees: Non-Random (List of Businesses)	Residents: Random (Address-Based) Employees: Non-Random (List of Businesses)	Random (Address-Based)	Random (Address-Based)
Collection Type	Paper (Residents); Web (Employees)	Paper (Residents); Web (Employees)	Paper; Web	Web
Sample Size	165 (Residents); 163 (Employees)	451 (Residents); 204 (Employees)	519	500
Survey Dates	Fall, 2000	Spring, 2006	Spring, 2012	Spring, 2018
Attitudes	(1) Strongly Disagree; (2) Disagree; (3) Neutral; (4) Agree; (5) Strongly Agree	(1) Strongly Agree; (2) Somewhat Agree; (3) Somewhat Disagree; (4) Strongly Disagree; (5) Don't Know		
Priorities	(1) Not at All Important; (2) Not Important; (3) No Opinion; (4) Important; (5) Very Important	(1) Essential; (2) Very Important; (3) Somewhat Important; (4) Not at All Important; (5) Don't Know		
Income	1 under $20,000 2 $20,000-$39,999 3 $40,000-$59,000 4 $60,000-$79,000 5 $80,000-$99,999 6 $100,000 or more	1 Less than $10,000 2 $10,000 to $19,999 3 $20,000 to $29,999 4 $30,000 to $39,999 5 $40,000 to $49,999 6 $50,000 to $74,999 7 $75,000 to $99,999 8 $100,000 to $149,999 9 $150,000 or more		
Geography	Residential Zip Code	Residential Zip Code	Descriptive Category	Descriptive Category; Residential Zip Code

Preparation of the Data

We obtained by request from CCRPC staff the raw data for all four travel surveys. To facilitate our analysis, we created a combined dataset that stacked together the data from all four surveys. To address the change in the attitudinal and priority scales after 2000, we consolidated responses into binary categories and excluded (i.e., treated as missing) the neutral responses (**Table 2**).

Table 2 Consolidation of Attitudinal and Priority Questions for Comparable Treatment Over the Survey Series

	2000	**2006, 2012, and 2018**
Attitudes	(0) Strongly Disagree/Disagree (1) Agree/Strongly Agree Missing: Neutral	(0) Strongly Disagree/Somewhat Disagree (1) Somewhat Agree/Strongly Agree Missing: Don't Know
Priorities	(0) Not at All Important/Not Important (1) Important/Very Important Missing: No Opinion	(0) Not at All Important (1) Somewhat Important/Very Important/Essential Missing: Don't Know

Note: Missing values (neutral, no opinion, don't know) were excluded from all analyses.

The wording for survey questions collected over time remained either identical or essentially the same (i.e. minorly adjusted); we note significant exceptions.

The creation of a common geographic identifier was essential for our analysis. As noted in **Table 1**, residential zip code was collected in all years but 2012, while the 2012 and 2018 surveys collected a self-reported description of the residential geographic setting based on the following six categories: City, downtown with a mix of offices, apartments, and shops; City, residential neighborhood; Suburban neighborhood, with a mix of houses, shops, and businesses; Suburban neighborhood, with houses only; Small town/village; and Rural area.

To create a common geographic identifier across all four surveys, we examined residential population density based on zip code for 2000, 2006, and 2018, and relied on the self-reported category for 2012. The 2000 travel survey responses were assigned zip code population densities based on the 2000 Decennial Census, while the zip codes from 2006 and 2018 survey responses were assigned zip code population densities based on the 2010 Decennial Census. We created four categories for the geographic identifier (**Table 3**, **Figure 2**), condensing the six categories from 2012 into four (city, suburb, small town/village, or rural) and using category breaks for population density based on familiarity with the study area. Population densities across the zip codes did not significantly change between 2000 and 2010; as a result, the four categories were stable across the survey series (**Figure 3**, **Figure 4**). We retained respondents from zip codes entirely or partially within CC.

Table 3 Creation of the Common Geographic Identifier Across All Four Travel Surveys

Zip Code	Jurisdiction	2000 Population Density	2010 Population Density	Assigned Category
05401	Burlington	3,560	2,577	City
05402	Burlington	NA	NA	City
05403	South Burlington	944	1,056	Suburb
05404	Winooski	4,813	5,311	City
05405	Burlington	NA	NA	City
05408	Burlington	NA	NA	City
05445	Charlotte	86	91	Rural
05446	Colchester	465	415	Suburb
05451	Essex	NA	NA	Suburb
05452	Essex	432	461	Suburb
05453	Essex Junction	NA	NA	Suburb
05461	Hinesburg	108	111	Small Town/Village
05462	Huntington	43	45	Rural
05465	Jericho	133	134	Small Town/Village
05468	Milton	193	222	Small Town/Village
05477	Richmond	73	70	Rural
05482	Shelburne	280	288	Suburb
05489	Underhill	60	60	Rural
05494	Westford	55	52	Rural
05495	Williston	245	274	Suburb
05676	Waterbury/Bolton	86	93	Rural

Note: Population density is measured as persons per square mile. Population density calculated using the 2000 and 2010 Decennial Census Zip codes without population density information include those which are used only for postal service (i.e., do not contain a land area). Includes zip codes partially within Chittenden County.

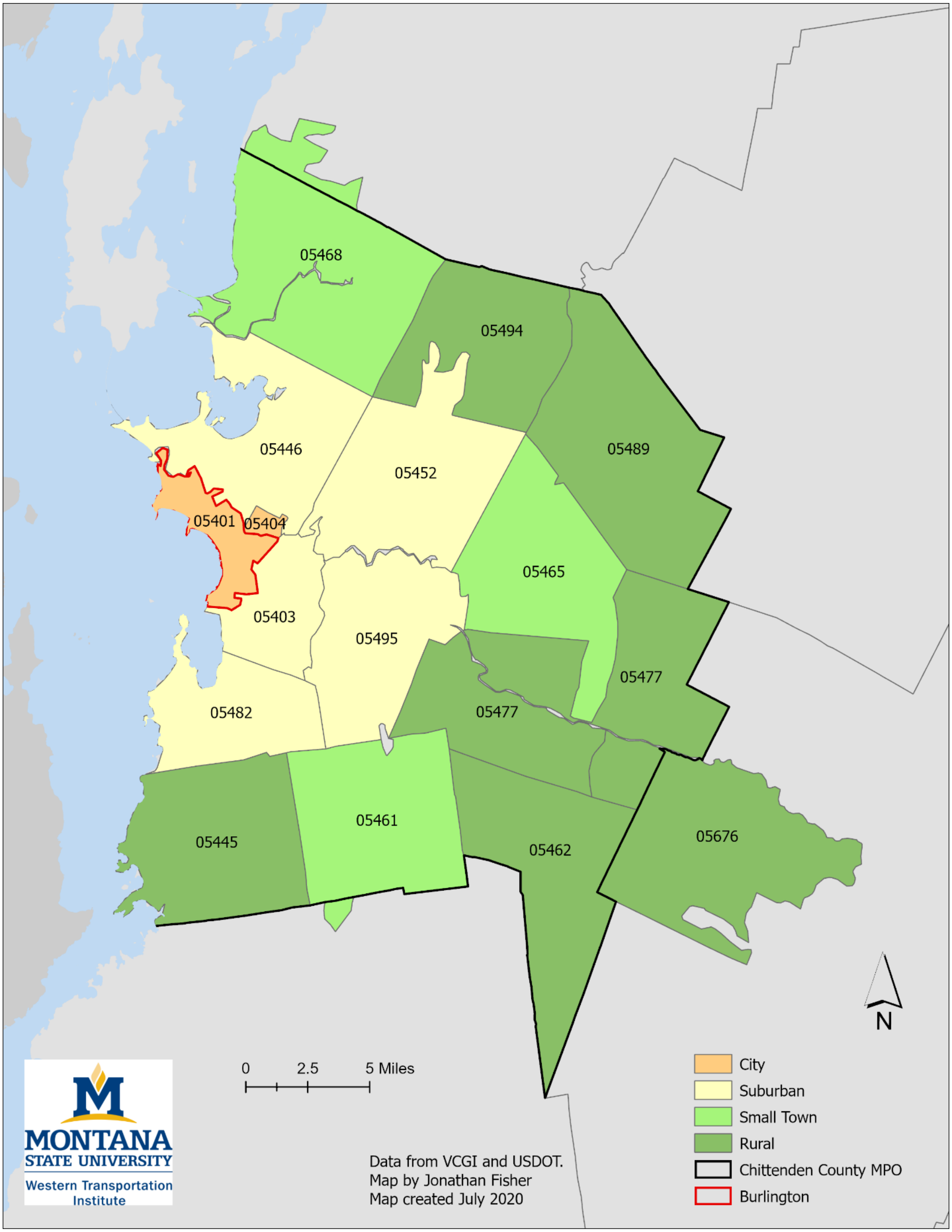

Figure 2 Classification of Chittenden County Zip Codes into Four Geographic Categories

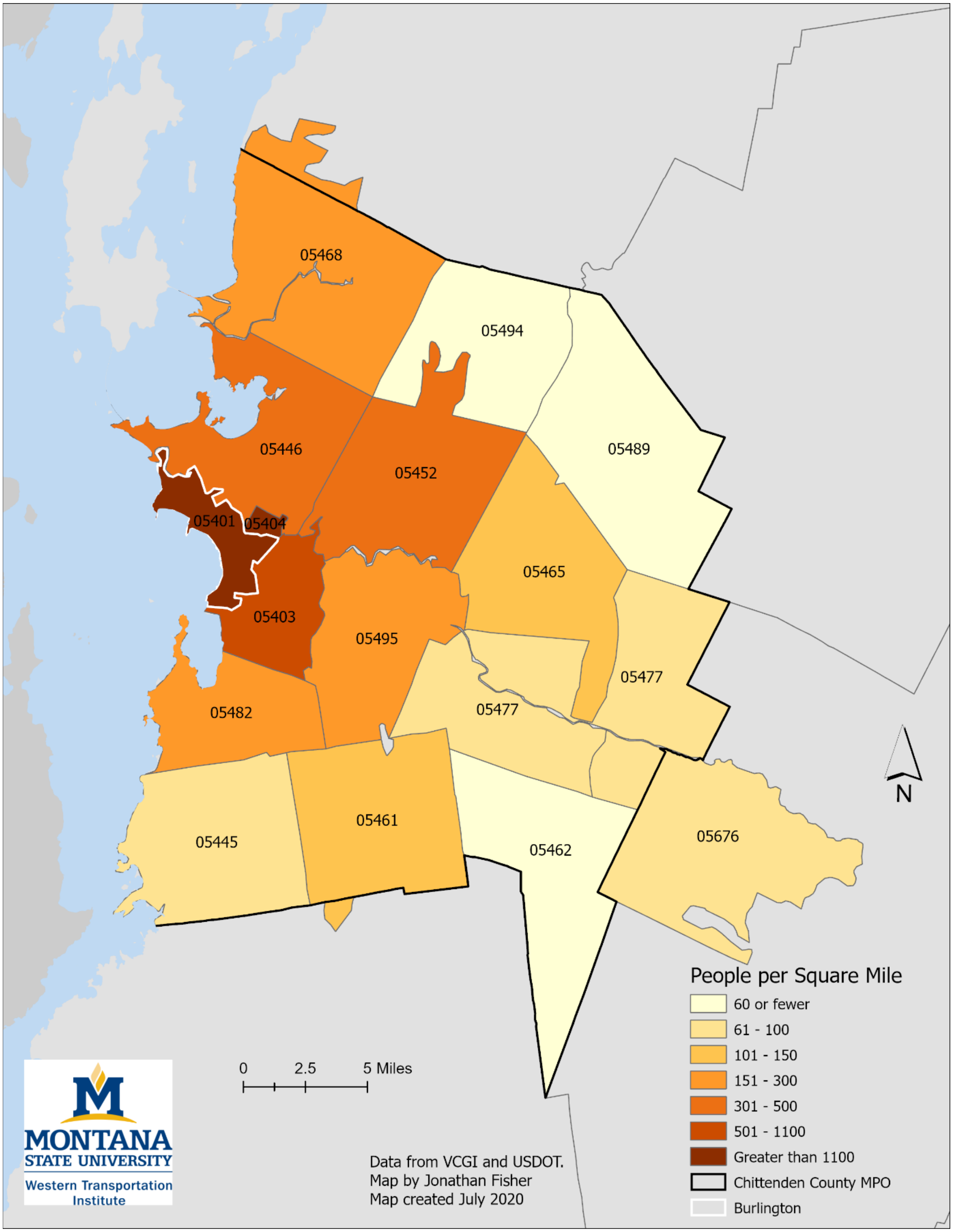

Figure 3 Population Density (Persons per Square Mile) by Zip Code for Chittenden County (2000)

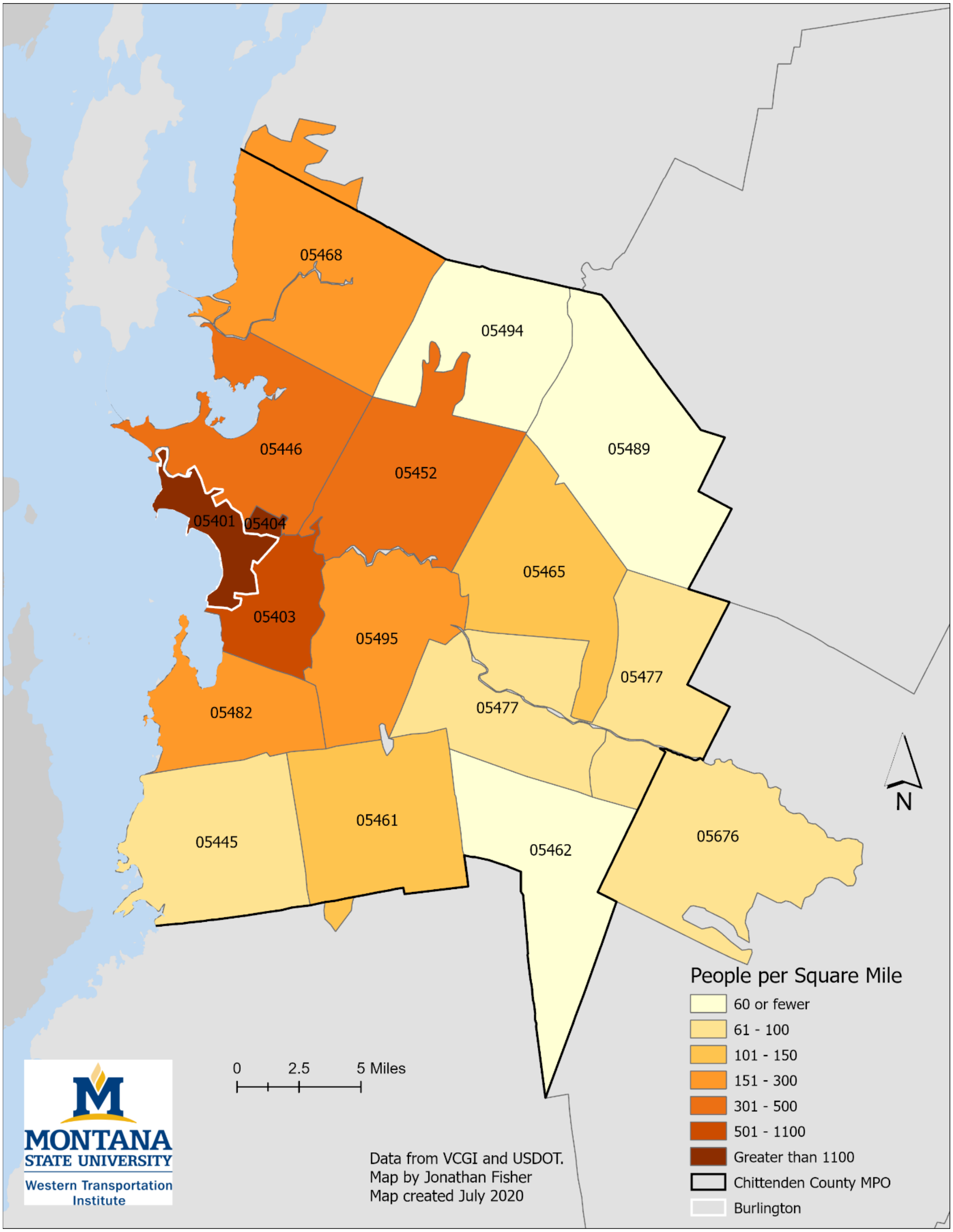

Figure 4 Population Density (Persons per Square Mile) by Zip Code for Chittenden County (2010)

Generation of Survey Weights

This project focused on the residential population of CC. As a result, respondents who reported a residential zip code outside of CC in 2000 (37 responses) or 2006 (47 responses) were excluded; the 2012 and 2018 samples consisted entirely of CC residents.

Focusing on the CC residential population enabled the generation of calibration weights using iterative proportional fitting (raking) with auxiliary data from the U.S. Census Bureau (**Table 4**). We weighted on seven variables, based on availability in both the surveys and auxiliary data as well as relevance for the project: 1) age; 2) gender; 3) employment status; 4) income; 5) household size; 6) household vehicles; and 7) geographic category (city, suburban, small town/village). Income was consolidated to two categories for the purposes of weighting the 2000 survey to align with the categories available in the auxiliary data. **Table 5** and **Table 6** summarize the auxiliary data in relation to the unweighted and weighted samples for each of the four surveys. We consider retainment for the analysis of the non-probabilistic sample from 2000 (both residents and employees) and the non-probabilistic portion of the 2006 sample (employees) justified after application of the calibration weights, though we recognize probabilistic random sampling as the ideal in survey practice.

Table 4 Summary of the Iterative Proportional Fitting for Calibration Weights

	First Iteration				Second Iteration			
	2000	2006	2012	2018	2000	2006	2012	2018
Age								
18-24	1.427	3.438	6.73	5.838	1.085	1.055	1.23	0.982
25-34	0.724	0.924	1.203	0.868	0.93	0.92	1.036	0.923
35-44	0.942	0.832	1.294	0.738	1.198	1.057	0.964	0.983
45-54	0.869	0.79	1.125	0.881	1.257	0.979	0.881	1.151
55-64	0.841	0.908	0.55	0.757	1.009	1.031	0.995	1.032
65 and over	2.985	1.045	0.523	0.916	0.618	0.959	0.935	0.969
Gender								
Female	1.218	0.917	0.979	0.934	1.041	1.031	0.968	0.992
Male	0.842	1.103	1.023	1.079	0.96	0.97	1.037	1.008
Employment Status								
Employed	0.918	0.875	0.883	0.929	0.928	0.952	0.971	0.955
Unemployed	1.364	2.812	1.557	1.795	1.078	1.236	0.857	1.086
Not in Labor Force	1.303	1.461	1.351	1.151	1.274	1.13	1.102	1.107
Income								
Less than $10,000		1.464	1.233	1.011		1.04	1.008	1.145
$10,000 to $49,999		1.044	0.941	1.146		1.008	1.031	1.047
$50,000 to $74,999		0.86	0.834	0.895		1.03	0.975	0.922
$75,000 to $99,999		0.796	1.069	1.054		1.001	1.024	0.949
$100,000 to $149,999		1.357	1.096	0.825		0.951	0.987	0.994
$150,000 or more		0.983	1.328	1.086		0.951	0.935	1.027
Less than $100,000	1.084				0.992			
$100,000 or More	0.614				1.071			
Household Size								
1 person	1.31	1.191	1.352	1.351	0.908	1.033	1.087	1.039
2 persons	0.92	0.877	0.832	0.972	1.022	0.996	0.985	0.98
3 persons	1.246	1.049	0.895	0.86	1.068	0.952	0.958	1.019
4 or more persons	0.78	0.985	1.125	0.825	1.04	1.005	0.954	0.969
Household Vehicles								
0 Vehicles	1.149	2.321	1.637	1.235	1.264	1.139	1.229	1.195
1 Vehicle	1.292	0.872	0.85	1.003	1.204	1.046	0.964	1.082
2 Vehicles	1.061	1	0.99	0.998	0.859	0.955	1.001	0.959
3 or More Vehicles	0.514	1.063	1.261	0.922	0.897	0.974	0.991	0.894
Geographic Category								
City	0.877	0.887	0.763	0.784	0.956	0.953	0.908	0.938
Suburban	1.309	0.971	1.12	0.961	0.999	1.013	1.029	1.006
Small Town/Village	0.612	1.114	1.383	1.747	1.063	1.016	1.071	1.079
Rural	1.244	1.441	1.098	1.512	1.048	1.068	1.087	1.066

Table 5 Summary of Auxiliary Data in Relation to Unweighted and Weighted Sample (2000 and 2006)

2000	Census	Unweighted	Weighted	2006	Census	Unweighted	Weighted
Geographic Category							
City	29.7%	28.9%	29.7%	City	30.8%	29.1%	30.8%
Suburban	43.6%	42.3%	43.6%	Suburban	42.7%	47.4%	42.7%
Small Town/Village	13.7%	19.9%	13.7%	Small Town/Village	14.1%	14.0%	14.1%
Rural	12.9%	8.9%	12.9%	Rural	12.4%	9.5%	12.4%
N	*153,012*	*291*	*285*	*N*	*162,013*	*608*	*534*
Age (18 and over)							
18-24	17.2%	12.0%	17.5%	18-24	16.5%	4.8%	16.4%
25-34	18.9%	26.1%	18.3%	25-34	15.4%	16.7%	15.7%
35-44	23.0%	24.4%	21.0%	35-44	19.8%	23.8%	19.0%
45-54	18.5%	21.3%	16.2%	45-54	20.9%	26.5%	20.1%
55-64	10.1%	12.0%	9.9%	55-64	14.0%	15.4%	13.9%
65 and over	12.3%	4.1%	17.2%	65 and over	13.3%	12.8%	15.0%
N	*112,058*	*291*	*285*	*N*	*117,524*	*604*	*534*
Gender							
Male	48.7%	60.5%	46.1%	Male	49.4%	45.6%	50.8%
Female	51.3%	39.5%	53.9%	Female	50.6%	54.4%	49.2%
N	*146,571*	*291*	*285*	*N*	*150,069*	*608*	*534*
Employment Status							
Employed	72.4%	88.0%	71.7%	Employed	71.0%	81.5%	70.2%
Unemployed	2.0%	1.7%	2.1%	Unemployed	3.0%	1.2%	3.1%
Not in Labor Force	25.5%	10.3%	26.2%	Not in Labor Force	26.0%	17.4%	26.7%
N	*108,220*	*291*	*285*	*N*	*113,644*	*605*	*534*
Household Size							
1 person	26.1%	14.8%	31.1%	1 person	27.5%	20.4%	28.5%
2 persons	35.0%	37.5%	33.4%	2 persons	34.8%	36.7%	34.5%
3 persons	16.3%	16.5%	14.9%	3 persons	16.7%	17.2%	16.6%
4 or more persons	22.6%	31.3%	20.7%	4 or more persons	20.9%	25.7%	20.4%
N	*56,397*	*291*	*285*	*N*	*59,150*	*583*	*534*
Household Vehicles							
0	9.0%	4.1%	8.8%	0	6.9%	2.5%	6.6%
1	37.2%	19.9%	37.0%	1	34.5%	30.0%	34.1%
2	41.1%	49.8%	41.5%	2	39.5%	45.9%	39.8%
3 or More	12.7%	26.1%	12.7%	3 or More	19.1%	21.6%	19.5%
N	*41,610*	*291*	*285*	*N*	*59,150*	*601*	*534*
Household Income							
Less than $100,000	89.1%	79.3%	89.7%	Less than $10,000	4.5%	1.8%	4.7%
$100,000 or More	10.9%	20.7%	10.3%	$10,000 to $49,999	40.2%	32.7%	41.0%
N	*41,607*	*285*	*285*	$50,000 to $74,999	20.1%	24.8%	19.9%
				$75,000 to $99,999	13.8%	19.6%	13.5%
				$100,000 to $149,999	14.6%	12.9%	14.3%
				$150,000 or more	6.7%	8.3%	6.6%
				N	*59,150*	*557*	*534*

Table 6 Summary of Auxiliary Data in Relation to Unweighted and Weighted Sample (2012 and 2018)

2012	Census	Unweighted	Weighted	2018	Census	Unweighted	Weighted
Geographic Category							
City	30.8%	30.5%	30.8%	City	30.8%	30.0%	30.8%
Suburban	42.7%	41.9%	42.7%	Suburban	42.7%	47.8%	42.7%
Small Town/Village	14.1%	13.0%	14.1%	Small Town/Village	14.1%	11.8%	14.1%
Rural	12.4%	14.6%	12.4%	Rural	12.4%	10.4%	12.3%
N	*162,013*	*515*	*456*	*N*	*162,013*	*500*	*413*
Age (18 and over)							
18-24	19.5%	2.9%	18.9%	18-24	19.8%	3.4%	20.8%
25-34	16.5%	13.7%	15.9%	25-34	17.0%	19.6%	16.3%
35-44	16.0%	12.3%	15.4%	35-44	14.0%	19.0%	13.8%
45-54	19.1%	17.0%	18.6%	45-54	15.9%	18.0%	15.1%
55-64	14.8%	27.0%	15.3%	55-64	16.0%	21.2%	15.9%
65 and over	14.2%	27.2%	15.8%	65 and over	17.2%	18.8%	18.1%
N	*125,670*	*519*	*456*	*N*	*132,584*	*500*	*413*
Gender							
Male	48.8%	50.3%	48.4%	Male	49.1%	48.8%	48.2%
Female	51.2%	49.7%	51.6%	Female	50.9%	51.2%	51.8%
N	*156,696*	*519*	*456*	*N*	*162,052*	*500*	*413*
Employment Status							
Employed	67.2%	71.1%	67.1%	Employed	66.9%	75.6%	66.6%
Unemployed	4.1%	2.5%	4.5%	Unemployed	2.6%	1.8%	2.7%
Not in Labor Force	28.7%	26.4%	28.4%	Not in Labor Force	30.5%	22.6%	30.7%
N	*129,654*	*515*	*456*	*N*	*136,047*	*500*	*413*
Household Size							
1 person	27.8%	24.3%	27.8%	1 person	28.5%	20.4%	30.1%
2 persons	36.8%	46.6%	36.8%	2 persons	38.5%	41.4%	37.9%
3 persons	16.3%	14.8%	16.1%	3 persons	14.9%	16.2%	14.1%
4 or more persons	19.1%	14.4%	19.4%	4 or more persons	18.2%	22.0%	17.9%
N	*62,265*	*515*	*456*	*N*	*65,400*	*500*	*413*
Household Vehicles							
0	7.3%	2.9%	6.7%	0	7.3%	3.0%	6.9%
1	33.9%	32.3%	33.5%	1	34.0%	27.6%	33.4%
2	41.6%	48.1%	42.0%	2	42.1%	53.2%	42.9%
3 or More	17.1%	16.7%	17.8%	3 or More	16.5%	16.2%	16.8%
N	*62,267*	*514*	*456*	*N*	*65,400*	*500*	*413*
Household Income							
Less than $10,000	5.7%	2.8%	5.9%	Less than $10,000	4.5%	1.9%	4.8%
$10,000 to $49,999	33.6%	27.1%	33.5%	$10,000 to $49,999	31.2%	19.9%	31.7%
$50,000 to $74,999	19.4%	25.4%	19.4%	$50,000 to $74,999	17.3%	21.3%	17.8%
$75,000 to $99,999	15.4%	17.8%	15.5%	$75,000 to $99,999	14.2%	15.5%	14.1%
$100,000 to $149,999	15.5%	17.0%	15.5%	$100,000 to $149,999	18.2%	24.7%	17.7%
$150,000 or more	10.4%	10.0%	10.3%	$150,000 or more	14.6%	16.7%	13.9%
N	*61,765*	*472*	*456*	*N*	*65,396*	*413*	*413*

Factor Identification and Cluster Segmentation

As noted earlier, this survey series was focused on transportation attitudes and priorities for regional transportation planning; all four CCRPC survey instruments were organized around the attitudinal and priority categories summarized in **Table 7**.

Table 7 Summary of Attitude and Priority Questions by Category for the Survey Series

	2000	2006	2012	2018
Attitudes				
Highway/Auto Travel	13	13	13	14
Public Transportation Systems	9	9	10	12
Bicycling and Walking	9	9	10	10
Transportation Behavior	10	8	10	13
Quality of Life, the Environment, and Economy	8	12	8	7
Transportation Planning Activities	4	3	3	0
Total	***53***	***54***	***54***	***56***
Priorities				
Highway Initiatives	4	4	4	4
Expanding Public Transportation Services/Facilities	5	6	8	10
Improved Bike/Walk Facilities	7	7	7	8
Incentives to Use Transportation Alternatives	7	6	8	8
Preserving the Condition of Existing Roads, Bridges, Sidewalks, Bike Paths, and Public Transportation Services and Facilities	6	7	7	7
Improved Safety	7	8	8	8
Minor Highway Efficiency Projects	5	5	5	4
Total	***41***	***43***	***47***	***49***

Note: Totals represent the number of questions in each category.

Many of the survey questions were overlapping in nature, as is common for opinion surveys. As a result of this high degree of correlation among subsets of the questions, the survey series was well-suited to the application of the factor identification and cluster segmentation techniques. Factor identification is a tool for deriving a new set of uncorrelated factors from a larger set of correlated variables. We chose to allow expectations and prior research to guide our generation of factors and elected to manually create factors. To do this, we generated row means (the mean of the variables listed) for the question sets described in **Table 8**; this was enabled because, as summarized in **Table 2**, each of these questions was transformed into a binary (0/1) response. Specifically, we grouped the question sets and then calculated the row means based on available data. As a result of changes in the survey instruments over time (see Overview of the Data above), some of the factors we generated were based on a different number of questions across the survey series. For example, Factor 1 is based on the row means for five questions in 2000 and 2006, seven questions in 2012, and nine questions in 2018 (**Table 8**). Specifically, Factors 2, 5, 6, and 7 include question sets that did not have varying availability across the survey series, while Factors 1, 3, 4, and 8 had one or more question change in availability. While this introduces some variability in the factor definitions across the survey years, we felt the benefit of incorporating more data when available was beneficial.

We assessed this approach using the Kuder-Richardson reliability coefficient for dichotomous variables, where a higher coefficient indicates greater reliability of the question set as a factor. **Table 8** summarizes the eight factors, along with their availability across the survey series and the reliability coefficient (alpha) for each factor based on the pooled sample. All of the factors have reliability coefficient indicating these factors serve as reliable constructs; the only factor with an alpha below 0.6 (perceives car as only option) was based on two questions perceived as a strong fit for a unique and highly interpretable factor.

Table 8 Summary of Factor Identification by Survey Question, Availability, and Kuder-Richardson's Reliability Coefficient

	Availability			
	2000	2006	2012	2018
Factor 1: Would Change Travel Behavior with Change in Conditions; Pooled K-R α=0.719				
I would walk more often if safe sidewalks were provided	x	x	x	x
If it cost more to drive my car, I would make fewer trips	x	x	x	x
I would take the bus if the routes and schedule were convenient for me	x	x	x	x
I would walk to work, school, shopping, or other activities if they were close enough	x	x	x	x
I would walk more often if sidewalks were provided	x	x	x	x
I would join a car sharing organization if the vehicle locations were convenient for me			x	x
I would bike more often if bike paths were provided			x	x
I would take the bus if there were better passenger facilities at bus stops throughout the system				x
I would take the bus if I felt safe and comfortable walking to and from bus stops				x
Factor 2: Perceives Car as Only Option; Pooled K-R α=0.515				
Nothing will replace my car as my main mode of transportation	x	x	x	x
When deciding how to make a typical daily trip, my car is the only safe, convenient, and affordable mode available to me	x	x	x	x
Factor 3: Concerned about Congestion, Safety, and Environmental Impacts; Pooled K-R α=0.652				
Traffic congestion affects the majority of trips I make	x	x	x	x
Traffic congestion gets noticeably worse every year	x	x	x	x
I often drive on back roads and residential streets to avoid congested highways	x	x	x	x
I am often delayed by road construction, accidents, or special event traffic	x	x	x	x
Driving in Chittenden County becomes more dangerous each year	x	x	x	x
The noise and emissions from cars, buses and trucks seem to be getting worse every year	x	x	x	x
The noise and emissions from cars, buses and trucks are an environmental problem		x	x	x
There is a significant amount of cut through traffic in my neighborhood	x	x	x	x
The streets in my neighborhood are safe and pleasant [RECODED]	x	x	x	x
Enough is being done to address the transportation needs of children, elderly, disabled, and low-income [RECODED]	x	x	x	x
Factor 4: Transit/Bike/Walk Enthusiast; Pooled K-R α=0.851				
Bus route and schedule information is accessible	x	x	x	x

	Availability			
	2000	2006	2012	2018
I feel safe riding the bus	x	x	x	x
The bus operators are always courteous towards the passengers	x	x	x	x
Overall, I am very satisfied with the bus system	x	x	x	x
Buses operate when I need to travel		x	x	x
Buses operate where I need to travel		x	x	x
CCTA/GMT has enough bus shelters		x	x	x
The buses are always clean		x	x	x
The bus system provides efficient connections to other travel modes and services		x	x	x
The amount I pay for bus fare is reasonable			x	x
The sidewalks and bike paths in my neighborhood, town or city are in good condition	x	x	x	x
There are enough sidewalks in my city or town	x	x	x	x
There are enough separated bike paths and/or bike lanes along roads in my city or town	x	x	x	x
I live close enough to walk to work, schools, shopping, services, or recreational/ entertainment opportunities	x	x	x	x
I feel safe when crossing a road on foot	x	x	x	x
Traveling by bicycle is safe for teenagers and adults	x	x	x	x
Traveling by bicycle is safe for children	x	x	x	x
Overall, walking is a pleasant experience in Chittenden County	x	x	x	x
Overall, traveling by bicycle is a pleasant experience in Chittenden County	x	x	x	x
Public bike racks are available where I need them			x	x
Factor 5: Prioritizes Highway Improvements; Pooled K-R α=0.780				
Adding more travel lanes to congested roads	x	x	x	x
Building more freeways (interstate type highways) to serve trucks, statewide through traffic and town-to-town Chittenden County traffic	x	x	x	x
Building more local roads to provide additional travel route options within and between adjacent municipalities	x	x	x	x
Providing new interstate interchanges	x	x	x	x
Factor 6: Prioritizes General Roadway Improvements; Pooled K-R α=0.703				
Repaving existing roads	x	x	x	x
Fixing bridges in poor condition	x	x	x	x
Repainting road lines	x	x	x	x
Improving road signage	x	x	x	x
Fixing dangerous intersections by installing stop signs, traffic signals, roundabouts, pedestrian signals, or reconstructing lanes	x	x	x	x
Reducing sharp corners and blind spots on highways	x	x	x	x
Installing medians that prevent left turns along major highways	x	x	x	x
Adding turning lanes at intersections	x	x	x	x
Improving traffic signal timing and better coordination of traffic signals in close proximity to each other	x	x	x	x
Installing roundabouts	x	x	x	x
Providing traveler information	x	x	x	x
Reducing the number of access driveways along major roadways	x	x	x	x
Factor 7: Prioritizes Incentives for Alternatives; Pooled K-R α=0.726				
Improving carpool ride-matching services	x	x	x	x

	Availability			
	2000	2006	2012	2018
Encouraging employers to pay employees subsidies to carpool/vanpool/take the bus	x	x	x	x
Providing guaranteed ride home programs for carpoolers who have to work late or leave work early	x	x	x	x
Vanpool transportation provided by your employer	x	x	x	x
Providing preferential parking spaces at work for those who carpool	x	x	x	x
Providing more park and ride lots	x	x	x	x
Factor 8: Prioritizes Improvements for Transit, Biking, and Walking; Pooled K-R α=0.919				
Increasing the frequency and number of hours per day the existing buses run	x	x	x	x
Making the buses more attractive and comfortable	x	x	x	x
Providing heated and lighted bus shelters	x	x	x	x
Expanding transit to and between all suburban towns in the County	x	x	x	x
Providing express transit to rural towns and park and ride lots	x	x	x	x
Encouraging development that provides housing, employment, and services within walking distance of transit stops	x	x	x	x
Expanding transit to regions outside of Chittenden County			x	x
Offering real-time information about the next bus arrival times			x	x
Giving buses priority at traffic lights so that transit routes can run faster				x
Providing enhanced passenger facilities, such as the new Downtown Transit Center or the expanded shelters at Champlain Mill				x
Providing bike paths separate from roadways	x	x	x	x
Providing bike lanes along existing roads	x	x	x	x
Providing bicycle amenities such as bike racks, bike shelters and lockers	x	x	x	x
Fixing existing sidewalks that are in poor condition	x	x	x	x
Providing new sidewalks	x	x	x	x
Encouraging development that locates jobs, housing, schools, services, and recreation within walking distance of each other	x	x	x	x
Provide amenities such as green strips, benches, trees, and other landscaping to improve the pedestrian environment	x	x	x	x
Improving crosswalks and pedestrian signals to make crossing streets safer and easier				x
Providing sidewalks and bike paths	x	x	x	x
Slowing traffic using calming devices such as speed humps, bump outs or narrow streets with green belts and trees	x	x	x	x
Improving cross walks	x	x	x	x
Providing more Park-and-Ride lots served by public transit			x	x
Providing convenient car share locations			x	x
Upgrading existing sidewalks	x	x	x	x
Upgrading existing bike paths	x	x	x	x
Clean and repair bus stops/shelters	x	x	x	x
Replacing older buses		x	x	x

Note: Factors were calculated using row means based on available data. As a result of changes in the survey instruments over time, Factors 1, 3, 4, and 8 were based on a varying number of questions across the survey series.

Using the eight factors (**Table 8**), we then applied k-means cluster analysis to the pooled sample to ensure the same cluster structure across the survey years. We segmented respondents across three modal orientation groups and assigned the following labels: 1) Car Oriented; 2) Car

Tolerant; and 3) Alternative (Transit/Bike/Walk) Oriented. Factor identification and cluster segmentation are discussed further in the review of literature presented below in Chapter 3.

Table 9 and **Figure 5** summarize the mean scores for the eight factors across the three modal orientations for the pooled 2000-2018 sample. The Car Tolerant cluster comprises about half (49%) of the pooled sample, while the Alternative Oriented (28%) and Car Oriented (23%) clusters split the remaining half. Across the eight factors, the Car Tolerant cluster tends to vary its alignment between the Alternative Oriented and Car Oriented clusters. The Car Tolerant cluster is similar to the Alternative Oriented cluster on Factor 1 (Would Change Travel Behavior with Change in Conditions), Factor 7 (Prioritizes Incentives for Alternatives), and Factor 8 (Prioritizes Improvements for Transit, Biking, and Walking). Meanwhile, it is similar to the Car Oriented cluster on Factor 2 (Perceives Car as Only Option) and Factor 5 (Prioritizes Highway Improvements). There are less significant differences across the three clusters for Factors 3 (Concerns about Congestion, Safety, and Environmental Impacts), Factor 4 (Transit/Bike/Walk Enthusiast), and Factor 6 (Prioritizes General Roadway Improvements).

To further describe the clusters, **Table 10** summarizes the binary tabulations for the key sociodemographic variables used for calibration weighting (**Table 5** and **Table 6**) across the three modal orientations for the pooled 2000-2018 sample. The Alternative Oriented cluster skews toward the city, younger age groups, fewer (especially zero) vehicles, and the lowest income quintile. Meanwhile, the Car Oriented cluster skews toward the suburbs, older age groups, more men, higher employment, more vehicles, and the higher income quintiles. In many cases, the tabulations for the Car Tolerant cluster falls in between those for the other two clusters.

Table 9 Share of Affirmative Responses for the Eight Factors by the Three Modal Orientations across the Survey Series

	Pooled (All Years)			
	Pooled Sample	Alternative Oriented	Car Tolerant	Car Oriented
Total (N)	***1,582***	***448***	***777***	***357***
Share of Sample	***NA***	***28%***	***49%***	***23%***
Factor 1: Would Change Travel Behavior with Change in Conditions	68%	80%	71%	40%
Factor 2: Perceives Car as Only Option	68%	17%	89%	91%
Factor 3: Concerned about Congestion, Safety, and Environmental Impacts	59%	57%	65%	48%
Factor 4: Transit/Bike/Walk Enthusiast	56%	60%	53%	58%
Factor 5: Prioritizes Highway Improvements	69%	44%	83%	70%
Factor 6: Prioritizes General Roadway Improvements	90%	88%	94%	81%
Factor 7: Prioritizes Incentives for Alternatives	79%	84%	92%	40%
Factor 8: Prioritizes Improvements for Transit, Biking, and Walking	87%	91%	93%	65%

Note: Percentages represent the row mean for each factor's binary (0/1) question set.

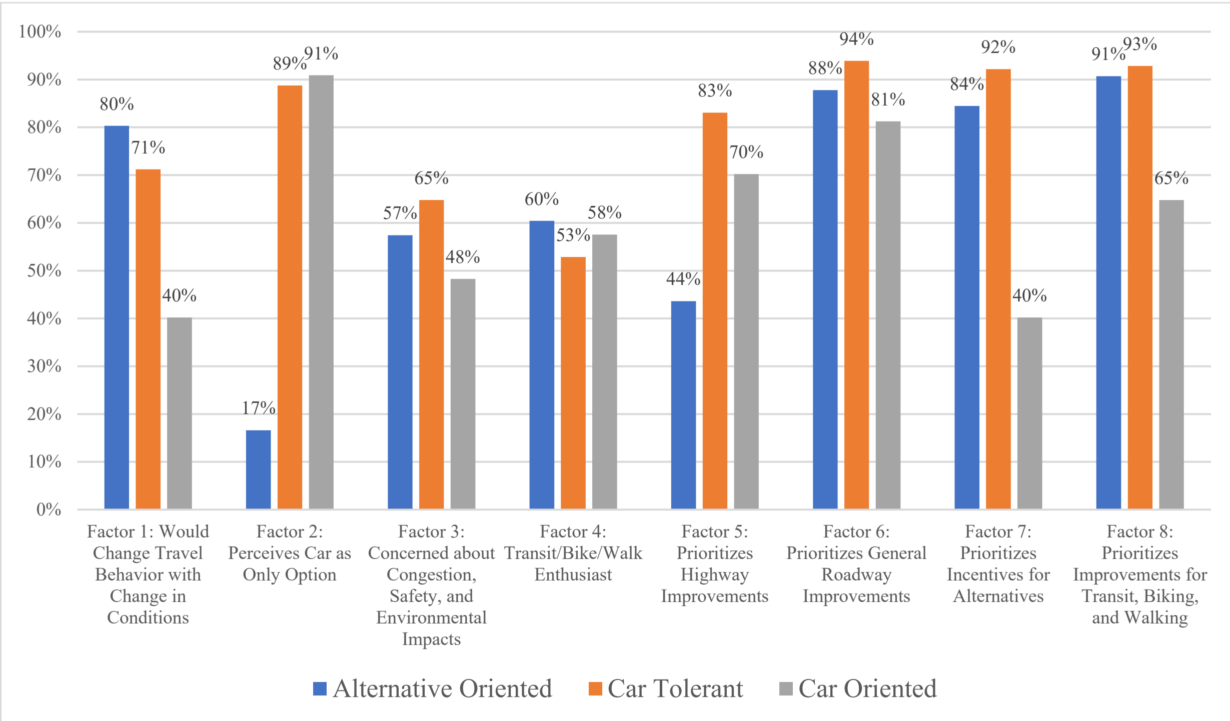

Figure 5 Binary Tabulations for the Eight Factors by the Three Modal Orientations for the Pooled Sample (All Years)

Table 10 Binary Tabulations for Key Sociodemographics by the Three Modal Orientations for the Pooled Sample

Pooled (All Years)	**Alternative Oriented**	**Car Tolerant**	**Car Oriented**
Total (N)	***448***	***777***	***357***
Share of Sample	***28%***	***49%***	***23%***
Geographic Category			
City	49%	22%	16%
Suburban	33%	47%	53%
Small Town/Village	10%	17%	14%
Rural	7%	14%	17%
Age (18 and Over)			
18-24	23%	18%	12%
25-34	21%	15%	14%
35-44	18%	17%	17%
45-54	18%	16%	23%
55-64	12%	15%	17%
65 and over	7%	20%	16%
Gender			
Male	51%	48%	55%
Female	49%	52%	45%
Employment Status			
Employed	68%	69%	75%
Unemployed	7%	3%	0.4%
Not in Labor Force	26%	28%	24%
Household Size			
1 Person	29%	29%	23%
2 Persons	36%	37%	39%
3 Persons	16%	15%	18%
4 or More Persons	19%	19%	21%
Household Vehicles			
0	14%	1%	0%
1	37%	37%	24%
2	39%	43%	50%
3 or More	10%	19%	26%
Household Income (Quintiles)			
1st (Lowest)	32%	18%	10%
2nd	17%	22%	13%
3rd	17%	19%	27%
4th	22%	26%	28%
5th (Highest)	12%	15%	22%

Models and Hypotheses

The modal orientations described above were employed in our investigation of nine outcomes across three categories: 1) travel indicators; 2) telecommunications; and 3) planning priorities. The following discussion describes the modeling approach for each.

Travel Indicators

We examined three travel indicators: household vehicles, mode use, and use of commuter benefits. Household vehicle ownership was the only key travel indicator available across the entire survey series, while collection of mode use (main and other modes) and commuter benefits was limited to 2012 and 2018. We focused the mode use groupings around a subset of four options, and the commuter benefit analysis around a subset of two commuter benefits:

Main Mode: *Which transportation option do you use most often?* ***Other Mode(s):*** *Which other transportation options have you used in the past month? Drive alone in a car you own/lease; Bus (CCTA/GMT); Bike; Walk*
Commuter Benefits: *Which of the following commuter benefits does your employer offer? Which do you personally use? Free or subsidized parking; Free or subsidized transit or shuttle use*

We used a single-equation ordered logistic regression to model household vehicle ownership, and a single-equation multinomial logistic regression to model mode use. The analysis of commuter benefits was more limited; ideally, we could have examined the commute mode outcome with regression analysis. However, because the survey instruments did not collect commute mode information separately from commuter benefits, commute mode could only be inferred from information provided about commuter benefit use. More specifically, commute mode could only be inferred from those reporting the offer of a mode-specific commuter benefit (i.e. driving to work based on reported use of free or subsidized parking). As a result, we focused on simply tabulating the offer and use of car parking and transit benefits. The following descriptions summarize the variables expected to be significantly associated with the three outcomes of interest:

Equation 1:
Household Vehicles = f(Age, Gender, Income, Household Size, Geographic Location, Modal Orientation, Survey Year)

Equation 2:
Mode Use = f(Age, Gender, Income, Household Size, Geographic Location, Modal Orientation, Survey Year)

Where Mode Use groups are defined as:
(0) Regular Driver – No Occasional Transit, Bike, or Walk;
(1) Regular Driver – Occasional Transit, Bike, and/or Walk; and
(2) Regular Transit, Bike, and/or Walk Use

Equation 3:
Commuter Benefit Use = f(Modal Orientation)
Where Commuter Benefit groups include:
(1) Car Parking
(2) Transit

Telecommunications

We used single-equation binary logistic regression to model both the availability of teleworking and the reduction of trips made due to use of the internet. In addition, we tabulated results for questions regarding the desire to telecommute (only collected in 2000 and 2006) and the offer and use of teleworking (only collected in 2012 and 2018). The telecommunications questions were asked in the following way:

Telework Availability: *Do you have the type of job that could be done at home?*
Telework Desire: *[If Telework Availability=Yes] I would like to work at home some or all of the time if given the opportunity.*
Telework Offer: *Which of the following commuter benefits does your employer offer? Which do you personally use? Telecommuting*
Internet Trip Reduction: *I have reduced the number of trips I made by using the internet for shopping, to pay bills, to take courses or for work*

Equation 4:
Telework Availability = f(Age, Gender, Education, Employment Sector, Employment Status, Income, Geographic Location, Modal Orientation, Survey Year)

Equation 5:
Internet Trip Reduction = f(Age, Gender, Education, Income, Geographic Location, Modal Orientation, Survey Year)

Planning Priorities

We focused on two assessments of planning priorities: 1) regional spending in relation to public opinion on the allocation of resources; and 2) public support for increasing gas taxes to pay for highway versus non-highway projects.

We compiled information from the CCRPC Transportation Improvement Program (as actually obligated) (hereafter “TIP (Obligated)”) for fiscal years (“FY”) 2000 to 2018 to assess spending by category. The TIP is a “prioritized, fiscally-constrained, and multi-year list of federally-funded, multimodal transportation projects and operations” for the region (Chittenden County Regional Planning Commission 2020). Due to annual variability in spending by category, we chose to focus on spending across the entire FY 2000 to FY 2018 timespan. The TIP (Obligated) documentation organized spending into the following categories:

- *Paving*
- *Bridge*
- *Roadway Corridor Improvements*
- *Safety/Traffic Operations/ITS*
- *New Facility/Major Roadway Upgrades*
- *Bike/Pedestrian*
- *Transit*
- *Intermodal*
- *Stormwater/Environmental*
- *Rail*
- *Other*

We sought to align as many of these categories with those included in the survey series as possible. As mentioned above, assessment of the relative prioritization of planning categories changed over the course of the survey series, from randomized pairings in 2000 to rankings in 2006 and 2012 and a distribution of points in 2018. We chose to focus on the distribution of points in 2018 as the most interpretable for the purposes of comparison to spending in the TIP. The survey instrument collected this information in the following way:

Given 100 points to distribute, assign points to each of the following initiatives based on how important each is to you. You must distribute all your points.

- *Highway Initiatives*
- *Expanded Public Transportation Service*
- *Improved Bike/Walk Facilities*
- *Incentives to Use Transportation Alternatives*
- *Preserving the Condition of Existing Roads, Bridges, Sidewalks, Bike Paths and Public Transportation Services and Facilities*
- *Improved Safety*
- *Minor Highway Efficiency Projects*

We compared the mean points assigned to each category by the survey sample as a whole, as well as by each modal orientation, in relation to the proportion of TIP spending in each comparable category. We limited our comparison to the three categories most clearly aligned between the TIP (Obligated) and survey instrument:

- *New Facility/Major Roadway Upgrades* → *Highway Initiatives*
- *Bike/Pedestrian* → *Improved Bike/Walk Facilities*
- *Transit* → *Expanded Public Transportation Service*

An important caveat to this analysis is the following qualification provided in the TIP (Obligated) documentation: "Many of the projects listed in the categories Safety/ Traffic Operations/ ITS, Roadway Corridor Improvements, New Facility/ Major Roadway Upgrade, and Paving also include improvements to bicycle and/or pedestrian facilities" (Chittenden County Regional Planning Commission 2020). As a result, we recognize that the spending reported in the TIP (Obligated) for Bike/Pedestrian projects may under-count projects supporting those biking and walking in the community. At the same time, some of the other survey categories could also support biking and walking as well (e.g. Incentives to Use Transportation Alternatives; Preserving the Condition of Existing Roads, Bridges, Sidewalks, Bike Paths and Public Transportation Services and Facilities; and Improved Safety). As a result, we recognize that many transportation projects are multifaceted and multimodal in nature and may defy simple categorization. However, for the purposes of understanding the broad patterns of regional transportation spending in relation to public opinion on resource allocation, we felt the method employed here was defensible.

Finally, we evaluated support for increasing gas taxes based on the following two questions, which were collected across the survey series:

Support for Gas Tax Increase (Exclusive to Highway Purposes): *I support increasing gas taxes to help pay only for highway projects*

Support for Gas Tax Increase (Inclusive of Non-Highway Purposes)*: I support increasing gas taxes to pay for non-highway projects such as transit, bicycle, and sidewalk projects (2000) / I support increasing gas taxes to help pay for highways, transit, bicycle and sidewalk projects (2006, 2012, 2018)*

We note the adjustment in wording after 2000 for the second question but feel there is sufficient consistency to assess support for increasing gas taxes to spend on non-highway projects. We evaluated the four outcomes across the two survey questions (Agree/Agree, Agree/Disagree, Disagree/Agree, Disagree/Disagree) in relation to the modal orientations, and then used a single-question binary logistic regression to model the probability of expressing support for each type of gas tax increase.

Equation 6:
Support for Gas Tax Increase = f(Age, Gender, Education, Employment Status, Income, Geographic Location, Modal Orientation, Survey Year)

Chapter 3: Travel Indicators

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This chapter focuses on the analysis of three travel indicators (household vehicle ownership, mode use, and commuter benefit use) in relation to modal orientation, and is organized into three sections: a review of prior research, a presentation of results, and a discussion of the findings.

Literature Review

As mentioned in Chapter 2, we employed factor identification and cluster analysis to segment respondents in our dataset into three modal orientations. This methodological approach was informed by the deployment of segmentation in sustainable travel behavior scholarship (**Table 11**), an approach adopted from the field of marketing and informed by insights from the fields of psychology, sociology, and behavioral economics (Vij 2013). While travel behavior analysis has traditionally focused on the more "tangible predictors of behavior" (Vij 2013) such as sociodemographic and built environment measures (Van Acker, Mokhtarian et al. 2011), segmentation often takes advantage of less commonly available sociopsychological constructs, such as normative beliefs, as well as lifestyle measures relating to values and attitudes (Krueger, Vij et al. 2018). Individuals are assigned to groups with distinct characteristics, which enables concentrated marketing and its associated benefits (optimized allocation of limited resources, design of contoured strategies, and narrowing of focus to a priority audience) (Pasha and Winters 2020). As a result, campaigns to encourage sustainable travel behavior informed by segmentation are better equipped to confront "long ingrained lifestyles and deeply entrenched habits built around the use of the automobile" (Vij 2013); Anable (2005) provides a notably detailed discussion of interventions targeted for each of the study's segments.

We draw two key lessons from the traveler segmentation literature to date. The first is that sociopsychological and lifestyle measures are significant behavioral predictors, even after accounting for sociodemographic and built environment measures (Choo and Mokhtarian 2002, Van Acker, Mokhtarian et al. 2011, Vij 2013). The second is that significant progress on sustainable travel behavior adoption requires shifts in the distribution of modality styles; ignoring the sociopsychological and lifestyle measures underlying modality styles may lead to underperformance and missed targets. Indeed, Vij (2013) argues that incremental improvements in the transport system will results in gaps between programmatic predictions and outcomes "unless accompanied by corresponding shifts in individual modality styles"; Krueger, Vij, and Rashidi (2018) present simulated market shares of the modal orientations to further elucidate the impact of shifts in modality styles on mode shares. As is the case for the present project, most of the traveler segmentation literature utilizes cross-sectional data, which cannot discern causal relationships (e.g., explain whether behaviors create attitudes or whether attitudes lead to behavioral patterns). It is likely that, over time, there is a mutual influence in both directions (Molin, Mokhtarian et al. 2016).

The present study contributes to this line of scholarship in two main ways. First, while most of the segmentation literature to date has focused on large cities (often due to limited availability of belief, value, and attitudinal data), this project focuses on a small urban area. Second, this project applies segmentation to an original dataset receiving its first comprehensive scholarly treatment.

Table 11 Overview of Recent Vehicle & Mode Use Traveler Segmentation Literature

Author(s), Year	**2002 (Choo & Mokhtarian)**	**2005 (Anable)**	**2005 (Steg)**
Study Area	US (San Francisco, CA)	UK (Visitors to National Trust Properties)	Netherlands (Groningen and Rotterdam)
Recruitment Size (Sample Size)	8,000 (1,904)	1,222 (666)	(185 and 113)
Model Type	Factor and Cluster Analysis; Multinomial Logit	Factor and Cluster Analysis; Segment Profiles (Factor Score & Behavioral Tabulations)	Factor Analysis; Stepwise Regression
Outcomes of Interest	Vehicle Type	Driver's License; Vehicle Availability; Share of Trips by Car; VMT; Share Using Alternatives; Intent to Use Alternatives	Share of Commuting Trips by Car
Explanatory Variables	Age, Education, Employment Status, Employment Type, Income, Household Size (Children), Gender, Geographic Location, Licensed Drivers, Travel (by Air and Car), Workers	Age, Education, Employment Status, Gender, Household Composition, Income	Age, Gender, Income, VMT
Clusters or Key Factors	**Factors:** **Travel Attitudes** (Travel Dislike; Pro-High Density); **Personality** (Organizer; Calm); **Lifestyle** (Frustrated; Workaholic, Status Seeking); **Clusters:** ***Attitude -*** Affluent Professionals; Transit-Using Urbanites; Homemakers & Older Workers; Travel Haters; Excess Travelers; Adventurous Caro-Oriented Suburbanites; ***Personality & Lifestyle -*** New Family; Homebodies; Mobile Yuppies; Transit Advocates; Assistant VPs; Status Seeking Workaholics; Suburban & Stationary; Older & Independent; Middle-of-the-Roaders; Travel Lovin' Transit Users; Frustrated Loners	**Factors:** Morals Obligation to Use Car Less; Attachment to Cars; Car Dependence; Congestion Effect; Enjoyment of Driving; Self Efficacy; Perceived Control; Willingness to Pay; Concern for Externalities; Social Norms; Belief in Cars for Freedom; Cycling Attitudes; Green Identity; Nature Views; Anthropocentrism; Green Purchasing; Green Activism; **Clusters:** ***Car-Owning*** (Malcontented Motorists; Complacent Car Addicts; Die Hard Drivers; Aspiring Environmentalists); ***Non-Car-Owning*** (Car-Less Crusaders; Reluctant Riders)	**Factors:** Attractiveness of Car Use; Functions of Car Use; Attitude Towards Car Use; **Motives for Car Use:** Symbolic and Affective; Instrumental; Independence

Key Findings	Travel Attitude, Personality, Lifestyle, and Mobility Factors Should be Included with Traditional Demographic Variables to Model Vehicle Type Choice; Pro High-Density Attitude Associated with Small/Compact Cars; Status Seeking Lifestyle Associated with Sports Cars	Moral Norm and Psychological Attachment to the Car Should be Include in Models of Mode Choice; Traveler Segmentation Can Guide Efforts to Encourage the Use of Alternative Modes	Non-Instrumental (Symbolic and Affective, Independence) Motives for Car Use are Significant; People Do Not Only Drive Because it is Necessary
Author(s), Year	**2008 (Domarchi, Tudela & Gonzalez)**	**2009 (Diana & Mokhtarian)**	**2009 (Flamm)**
Study Area	Chile (University of Concepcion)	US (San Francisco, CA); France (Paris, Lyon, Lille, Marseille)	US (Sacramento, CA)
Recruitment Size (Sample Size)	400 (183)	8,000 (1,904); 550 (164)	4,000 (1,506)
Model Type	Multinomial Logit	Cluster Analysis; Tabulations	Regression (Unspecified)
Outcomes of Interest	Mode Use (Car and Transit)	Time (Weekly Hours) Using Cars & Transit	Vehicle Ownership; Fuel Economy; VMT; Annual Fuel Consumption
Explanatory Variables	Age, Gender, Income, Occupation, Vehicle Availability	Education, Income, Vehicle Ownership	Age, Education, Income, Household Size, Licensed Drivers, Pedestrian Environment, Residential Density
Clusters or Key Factors	**Car and Public Transportation:** Habit (10-point Index), Attitude (Expectance-Value), Affect (Semantic Differential)	**Factors: Car, Public Transportation, and Composite** (Objective, Subjective, and Relative Desired Mobility); **Clusters:** ***Study 1 -*** Heavily Car Oriented; Rather Car Oriented; More Transit Oriented; Light Travelers; ***Study 2 -*** Car Oriented; Transit Oriented; Neither Oriented; Both Oriented	**Factors:** Environmental Knowledge, Environmental Attitudes
Key Findings	Attitude, Habit, and Affective Appraisal Influence Mode Choice; Those With Strong Car Use Habit Do Not Develop Intention Before Car Use; Car Use Becomes Vicious Circle)	In General, Evidence for a Desire for Modal Consumption Balance; Ideal Levels of Mode Use May Depend on Modal Balance more than Overall Mobility	Environmental Knowledge and Attitudes Significantly Effect Vehicle Ownership and Use; Planners Should Highlight Connection Between Environmental Impacts and Travel Behavior via Social Marketing

Author(s), Year	**2010 (Hunecke, Haustein, Bohler & Grischkat)**	**2011 (Van Acker, Mokhtarian & Witlox)**	**2012 (De Vos, Derudder, Van Acker & Witlox)**
Study Area	Germany (Augsburg, Bielefeld, Magdeburg)	Belgium (University of Antwerp and Ghent University, Flanders)	Belgium (University of Antwerp and Ghent University, Flanders)
Recruitment Size (Sample Size)	11,028 (1,991)	(1,878)	(1,657)
Model Type	Principal Component & Cluster Analysis	Factor Analysis; Structural Equation Modeling	Factor Analysis
Outcomes of Interest	Mode Use (Car, Transit, Bicycle, Walking); Emission Estimates	Mode Choice (Leisure)	Mode Use (Leisure)
Explanatory Variables	Sociodemographic Lifecycle Groups; Geographic Location	Age, Education, Employment Status, Gender, Geographic Location, Licensure, Life Stage, Residential Density, Vehicle Ownership	Residential Dissonance (Urban, Rural); Mode Choice (Leisure)
Clusters or Key Factors	**Factors:** Public Transportation Control; Public Transportation Excitement; Car Attitude; Bicycle Attitude; Weather Resistance; Ecological Norm; Perceived Mobility Necessities; Openness to Change; **Clusters:** Public Transport Rejecters; Car Individualists; Weather-Resistant Cyclists; Eco-Sensitized Public Transport Users; Self-Determined Mobile People	**Factors:** ***Lifestyles -*** Culture Lover; Friends and Trends; Low-Budget & Active/Creative; Home-Oriented But Active Family; Home-Oriented Traditional Family; ***Residential -*** Open Space & Quietness; Car Alternatives; Accessibility; Safety & Neatness; Social Contact; ***Travel Attitudes -*** Frustrated Traveler; Pro-Environment; Reduced-Driving Social Expectations	**Factors:** Pro Bicycling/Walking; Car Accessibility and Parking; Pro Car; Pro Travel; Environmentally Aware; Accessibility Public Transit; Pro Public Transit; Accessibility Bicycling/Walking; Proximity of Shops, Bars, Etc.
Key Findings	Ecological Impact Varies Significantly by Attitude-Based Target Groups	Subjective Variables Explain An Important Share of Mode Choice for Leisure Trips; Planners Should Improve Image of Transit, Cycling, and Walking	Residential Dissonance is Relatively (51.4%) Prevalent; Improving Image of Alternatives & City Location Could Aid Urban Dissonants to Use Alternatives More
Author(s), Year	**2013 (Vij)**	**2016 (Molin, Mokhtarian & Kroesen)**	**2018 (Krueger, Vij & Rashidi)**
Study Area	Germany (Karlsruhe); US (San Francisco, CA); Chile (Santiago)	Netherlands	Australia (Adelaide, Brisbane, Melbourne, Perth, Sydney)
Recruitment Size (Sample Size)	317 (119); 26,350; 220	110,000 (2,548)	(516)
Model Type	Latent Class Choice Model	Latent Class Cluster Analysis	Latent Class & Latent Variable Model

Outcomes of Interest	Mode Choice (Work & Leisure); Transit Pass; Vehicle Ownership	Mode Use (Bicycle, Car, Bus/Tram/Metro, Train)	Mode Use, Vehicle Ownership, Bicycle Ownership, Walking Access Time to Transit
Explanatory Variables	Age, Gender, Employment Status, Household Size, Income, Internet Access, Marital Status, Parental Status, Race/Ethnicity	Age, City Size, Commute Days, Education, Employment Status, Gender, Household Composition, Income, Work Location, Vehicle Availability	Age, Employment Status, Gender, Geographic Location, Income, Household Children
Clusters or Key Factors	**Germany:** ***Individuals -*** Auto-Oriented; Choice Multimodals; Captive Multimodals; ***Households -*** Transit-Friendly Drivers; Multimodal Greens; Auto-Oriented Households; Bicycle-Friendly Drivers; **US:** Inveterate Drivers; Car Commuters; Moms in Cars; Transit Takers; Multimodals; Empty Nesters; **Chile:** Unimodal Auto Users; Unimodal Transit Users; Multimodal Users	**Factors:** ***Mode Perceptions*** (Pleasant, Convenient); ***Mode Attitudes*** (Transit Transfer Acceptability, Waiting Acceptability, Timeliness, Seat Availability, Planning Ease, Cost; Car Cost); **Clusters:** Car Multimodal; Bike Multimodal; Bike & Car; Car Mostly; Transit Multimodal	Factors: Normative Beliefs (Car Use; Transit Use; Walking; Ecological Impact of Mobility); Attitudes (Driving Enjoyment & Stress, Transit Enjoyment & Stress, Bicycle Mobility, Walking Enjoyment); Clusters: Transit Oriented; Car Oriented; Car & Bicycle Oriented
Key Findings	Modality Styles (Behavioral Predispositions Toward a Certain Mode/Set of Modes) Significantly Influence Travel & Activity Behavior; Gap Between Predicted & Observed Mode Shares May Be Due in Part to Overlooking of Modality Styles; Incremental Improvements in Transport System Without Shifts in Modality Style Distribution Will Results in Smaller Travel Behavior Changes than Predicted; System Shocks May Force Reconsideration of Travel & Shift Modality Styles	Perceptions & Modal Attitudes are Generally Congruent with Mode Use (i.e. Familiarity with Transit Leads to More Favorable Transit Attitude); Exclusive Car Users Have More Negative Perceptions & Attitudes of Alternatives	Changes in Normative Beliefs May Influence the Prevalence of Modality Styles & Eventually Translate into Changes in Travel Behavior

Results

The summary statistics for the household vehicle and mode use samples are compiled in **Table 12**. The household vehicle sample pools together the cross-sections from 2000, 2006, 2012, and 2018 and has a total of 1,582 observations. Only 5% of the sample has no private vehicle, while 61% has at least two vehicles. Meanwhile, the mode use sample pools together the cross-sections from 2012 and 2018 and has a total of 750 observations. About half of the sample reports the main mode of driving, with at least monthly use of transit, biking, and/or walking, while only 17% of the sample report relying on transit, biking, or walking as a main mode. The distribution of modal orientations is almost identical across the two samples, with the Car Tolerant cluster comprising half of each sample.

Table 12 Summary Statistics for the Household Vehicle and Mode Use Samples

Variable	Obs	Mean	Min	Max	Variable	Obs	Mean	Min	Max
Household Vehicles					***Mode Use***				
0 Vehicles	1,582	5%	0	1	Regular Driver - No Occasional Transit, Bike, Walk	750	32%	0	1
1 Vehicle	1,582	34%	0	1	Regular Driver - Occasional Transit, Bike, and/or Walk	750	51%	0	1
2 Vehicles	1,582	43%	0	1	Regular Transit, Bike, and/or Walk	750	17%	0	1
3 or More Vehicles	1,582	18%	0	1					
Age									
18-24	1,582	18%	0	1	18-24	750	20%	0	1
25-34	1,582	17%	0	1	25-34	750	17%	0	1
35-44	1,582	17%	0	1	35-44	750	15%	0	1
45-54	1,582	18%	0	1	45-54	750	17%	0	1
55-64	1,582	14%	0	1	55-64	750	16%	0	1
65 and older	1,582	15%	0	1	65 and older	750	16%	0	1
Gender									
Female	1,582	50%	0	1	Female	750	52%	0	1
Male	1,582	50%	0	1	Male	750	48%	0	1
Geographic Location									
City	1,582	29%	0	1	City	750	31%	0	1
Suburb	1,582	44%	0	1	Suburb	750	43%	0	1
Small Town/Village	1,582	14%	0	1	Small Town/Village	750	14%	0	1
Rural	1,582	13%	0	1	Rural	750	13%	0	1
Household Size									
1 Person	1,582	28%	0	1	1 Person	750	31%	0	1
2 Persons	1,582	37%	0	1	2 Persons	750	38%	0	1
3 Persons	1,582	16%	0	1	3 Persons	750	14%	0	1
4 or More Persons	1,582	19%	0	1	4 or More Persons	750	17%	0	1
Income Quintile									
1 (Lowest)	1,582	19%	0	1	1 (Lowest)	750	20%	0	1
2	1,582	19%	0	1	2	750	19%	0	1
3	1,582	21%	0	1	3	750	18%	0	1
4	1,582	16%	0	1	4	750	15%	0	1
5 (Highest)	1,582	26%	0	1	5 (Highest)	750	28%	0	1
Modal Orientation									
Alternative Oriented	1,582	30%	0	1	Alternative Oriented	750	31%	0	1
Car Tolerant	1,582	50%	0	1	Car Tolerant	750	48%	0	1
Car Oriented	1,582	20%	0	1	Car Oriented	750	21%	0	1

Variable	Obs	Mean	Min	Max	Variable	Obs	Mean	Min	Max
Household Vehicles					***Mode Use***				
Year									
2000	1,582	15%	0	1					
2006	1,582	31%	0	1					
2012	1,582	28%	0	1	2012	750	51%	0	1
2018	1,582	25%	0	1	2018	750	49%	0	1
Pooled Cross Sections (2000, 2006, 2012, 2018) Calibration Weights Applied					***Pooled Cross Sections (2012, 2018) Calibration Weights Applied***				

The binary tabulations across modal orientations for the household vehicle and mode use samples are compiled in **Table 13** as well as **Figure 6** and **Figure 7**. As expected, a much higher share of the Alternative Oriented cluster does not own a private vehicle (14%). In contrast, none of the respondents in the Car Oriented cluster report zero private vehicles. The between-group F test indicates that household vehicles differ significantly by modal orientation. The pattern of mode use also varies by modal orientation. A small share (8%) of the Alternative Oriented cluster reports being a regular driver report no transit, biking, or walking, while over half (53%) of the Car Oriented cluster falls into that mode use group. Meanwhile, as expected, the Alternative Oriented cluster relies on transit, biking, or walking as a main mode at a much higher rate (43%) than the other two clusters. To build upon these cross-tabulations, the regression models presented below attempt to isolate the association of modal orientation with household vehicles and mode use while holding additional relevant variables constant.

Table 13 Binary Tabulations for the Household Vehicles and Mode Use Samples by Modal Orientation

	Household Vehicles Sample				***Mode Use Sample***		
	Alternative Oriented	Car Tolerant	Car Oriented		Alternative Oriented	Car Tolerant	Car Oriented
Total (N)	448	777	357	Total (N)	211	365	174
Household Vehicles				***Mode Use***			
0 Vehicles	14%	1%	0%	Regular Driver - No Occasional Transit, Bike, Walk	8%	40%	53%
1 Vehicle	37%	37%	24%	Regular Driver - Occasional Transit, Bike, and/or Walk	49%	56%	41%
2 Vehicles	39%	43%	50%	Regular Transit, Bike, and/or Walk	43%	4%	6%
3 or More Vehicles	10%	19%	26%				
ANOVA Between Groups F Test: p=0.000				ANOVA Between Groups F Test: p=0.000			
Pooled Cross Sections (2000, 2006, 2012, 2018) Calibration Weights Applied				***Pooled Cross Sections (2012, 2018) Calibration Weights Applied***			

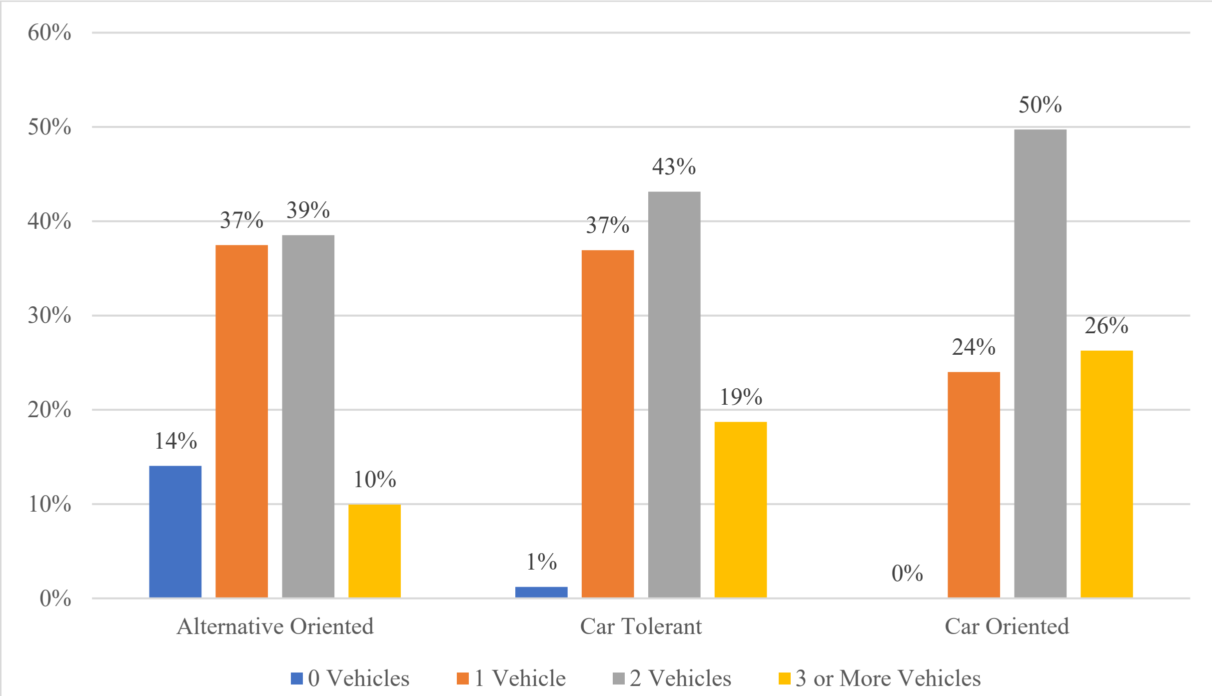

Figure 6 Binary Tabulations for Household Vehicles by Modal Orientation

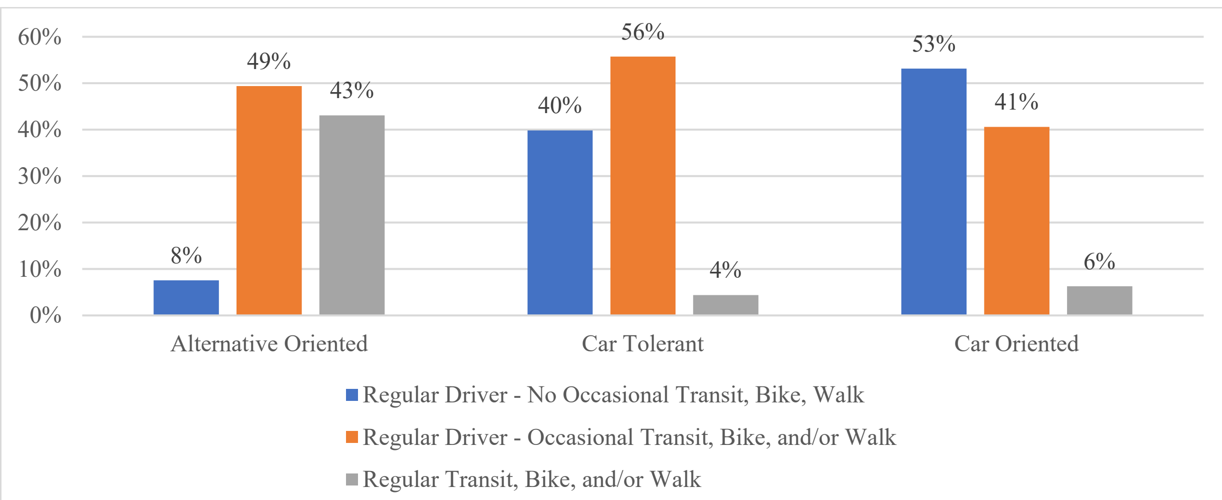

Figure 7 Binary Tabulations for Mode Use by Modal Orientation

The binary tabulations across modal orientations for the offer and use of car parking and transit commuter benefits are summarized in **Table 14** and **Figure 8**. Car parking benefits are more common than transit benefits (65% versus 20% for the pooled sample), and among those offered these benefits, car parking utilization is higher (90% versus 37%). While the offer of car parking does not significantly vary across the modal orientations (ANOVA Between Groups F Test p-value=0.741), utilization does (ANOVA Between Groups F Test p-value=0.000). As expected, the utilization of a car parking benefit is lowest among the Alternative Oriented cluster (79%), and highest among the Car Oriented (97%). The share of workers offered a car parking benefit did not significantly change between 2012 and 2018 (t-test p-value=0.205), but utilization decreased significantly, from 93% to 87%. Meanwhile, unlike for car parking benefits, the offer of a transit benefit does vary significantly by modal orientation. The highest share offered a transit benefit is for those in the Alternative Oriented cluster (28%) and the lowest is for those in the Car Oriented cluster (13%). Utilization follows a similar pattern, with 52% of those in the Alternative Oriented cluster who are offered a transit benefit reporting making use of it, compared to only 20% for the Car Oriented cluster. The share of workers offered and utilizing a transit benefit did not significantly change between 2012 and 2018 (t-test p-value=0.690 for offer and p-value=0.122 for use).

Table 14 Binary Tabulations for Commuter Benefit (Parking and Transit) Offer and Use Among Employed Chittenden County Residents by Modal Orientation

	Pooled Sample	Alternative Oriented	Car Tolerant	Car Oriented	2012	2018
Car Parking						
Offer (N)	602	148	297	138	292	310
Offer (%)	65%	67%	64%	67%	62%	68%
		ANOVA Between Groups F Test: p=0.741			T-test: p=0.147	
Use (N)	401	101	194	93	198	203
Use (%)	90%	79%	94%	97%	93%	87%
		ANOVA Between Groups F Test: p=0.000			T-test: p=0.044	
Transit						
Offer (N)	572	143	283	128	279	293
Offer (%)	20%	28%	19%	13%	19%	20%
		ANOVA Between Groups F Test: p=0.007			T-test: p=0.690	
Use (N)	121	44	57	18	63	58
Use (%)	37%	52%	32%	20%	44%	30%
		ANOVA Between Groups F Test: p=0.035			T-test: p=0.122	

Note: Tabulations limited to employed CC residents.

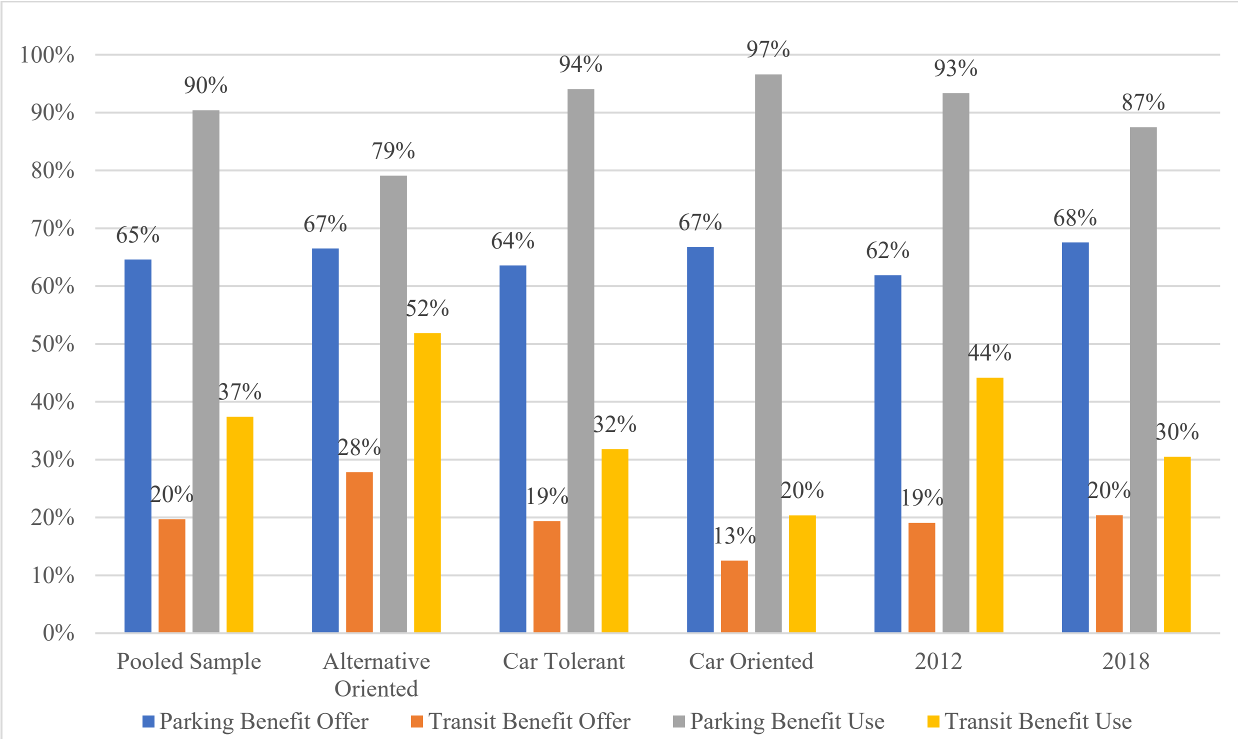

Figure 8 Share of Chittenden County Employed Residents Offered and Using Parking and Transit Benefits by Modal Orientation
Note: Tabulations limited to employed CC residents.

Table 15 presents the ordered logistic regression results for household vehicle ownership. The coefficients for the model have been transformed into odds ratios and may be interpreted as the odds of a one-unit increase in vehicle ownership associated with each level of the independent variable compared to its base level. For example, the odds of owning one household vehicle compared to zero is 2.3 times higher for those in the second income quintile compared to the first income quintile. The model suggests vehicle ownership is significantly associated with lower odds for middle age (25-34 and 35-44) but not for the upper age groups (45 and older), compared to the base of 18-24. Vehicle ownership is positively associated with being male compared to the base of female. Vehicle ownership is negatively associated with density (as captured in the geographic location variable), and positively associated with income and household size. Compared to the base year of 2000, the odds of owning more vehicles was significantly higher in each subsequent survey year. Even after controlling for (or holding constant) age, gender, geographic location, household size, income, and survey year, household vehicle ownership varies significantly across the model orientations. Compared to the Alternative Oriented cluster, the odds of owning more vehicles is significantly higher for those in the Car Tolerant and Car Oriented clusters. In terms of explanatory power, the pseudo-R2 for the model is 0.295, and it produces a proportional reduction in error (a measure of improving upon chance in predicting the outcome) of 0.323.

Table 15 Ordered Logistic Regression Results (Likelihood of 0, 1, 2, or 3 or More Household Vehicles)

Ordered Logistic Regression						
Probability of 0, 1, 2, 3 or More Household Vehicles						
	Odds Ratio	**Std. Err.**	**z**	**P>|z|**	**[95% Conf.**	**Interval]**
Age						
18-24	*base*					
25-34	0.6	0.1	-2.7	0.01	0.4	0.9
35-44	0.5	0.1	-3.5	0.00	0.3	0.7
45-54	0.8	0.2	-1.0	0.34	0.6	1.2
55-64	1.1	0.2	0.3	0.75	0.7	1.6
65 and older	0.8	0.2	-1.3	0.19	0.5	1.1
Gender						
Female	*base*					
Male	1.3	0.1	2.4	0.02	1.0	1.6
Geographic Location						
City	*base*					
Suburb	2.1	0.3	5.1	0.00	1.6	2.7
Small Town/Village	3.6	0.7	6.9	0.00	2.5	5.2
Rural	5.1	1.0	8.2	0.00	3.5	7.5
Household Size						
1 Person	*base*					
2 Persons	10.1	1.6	14.6	0.00	7.4	13.8
3 Persons	33.7	6.9	17.2	0.00	22.6	50.3
4 or More Persons	35.3	7.2	17.6	0.00	23.8	52.6
Income Quintile						
1 (Lowest)	*base*					
2	2.5	0.5	4.9	0.00	1.7	3.6
3	2.7	0.5	5.3	0.00	1.9	3.9
4	5.3	1.1	8.0	0.00	3.5	8.1
5 (Highest)	6.9	1.4	9.6	0.00	4.7	10.3
Modal Orientation						
Alternative Oriented	*base*					
Car Tolerant	2.1	0.3	5.8	0.00	1.6	2.7
Car Oriented	3.2	0.5	7.2	0.00	2.3	4.3
Year						
2000	*base*					
2006	1.8	0.3	3.5	0.00	1.3	2.5
2012	1.3	0.2	1.8	0.08	1.0	1.9
2018	1.3	0.2	1.7	0.09	1.0	1.9
Total Observations: 1,582; Pseudo R2: 0.295; Proportional Reduction in Error: 0.323						

Table 16 presents the multinomial logistic regression results for the mode use groups. As was the case for the ordered logistic regression above, the coefficients for the model have been transformed into odds ratios and may be interpreted as the odds of fitting into the Regular Driver – Occasional Transit, Biking, or Walking or Regular Transit, Biking, or Walking mode use group

compared to the base mode use group (Regular Driver – No Occasional Transit, Biking, or Walking). For example, the odds of relying on transit, biking, or walking as a main mode compared to relying on driving without occasional transit, biking, or walking are only 0.141 as high for those in the second income quintile compared to those in the first (lowest) quintile.

The model suggests that the odds of being a regular driver who occasionally uses transit, biking, or walking compared to a regular driver who does not use these alternatives is significantly lower for those 35 and older compared to the base age group of 18-24, but does not differ significantly for those 25-34. Males are more likely to be regular drivers who do not use alternatives, when compared to females. Those in lower density areas have lower odds of being a regular driver who uses alternatives. The odds do not significantly differ across income and household size categories (with the lone exception of lower odds for the fourth income quintile). The odds appear to have increased over time, with respondents in 2018 having higher odds of being a regular driver who occasionally uses transit, biking, or walking, compared to respondents in 2012.

Meanwhile, the odds of relying on transit, biking, or walking as a main mode are significantly lower for those 35 and older compared to the base of 18-24, but the odds do not significantly differ between men and women. The odds of relying on an alternative are lower in the lower density settings; an estimate for the Rural category was unavailable as no households in this geographic category had this outcome. The odds did not significantly differ by household size but were negatively associated with income. The odds do not appear to have changed over time.

Even after controlling for age, gender, geographic location, household size, income, and survey year, the odds for belonging to these mode use groups differs significantly across the modal orientation clusters. Compared to the base outcome of relying on driving as a main mode with no occasional transit, biking, and walking, the odds of reporting one of the two mode use groups that incorporated alternatives (occasional or regular use of alternatives) were both significantly lower for the Car Tolerant and Car Oriented modal orientations compared to the Alternative Oriented. In terms of explanatory power, this model had a pseudo-R2 of 0.361 and produced a proportional reduction in error of 0.246.

Table 16 Multinomial Logistic Regression Results (Likelihood of Belonging to One of Three Mode Use Groups)

Base Outcome: (0) Regular Driver - No Occasional Transit, Bike, or Walk						
	(1) Regular Driver - Occasional Transit, Bike, and/or Walk			**(2) Regular Transit, Bike, and/or Walk**		
	Odds Ratio	**Std. Err.**	**P>|z|**	**Odds Ratio**	**Std. Err.**	**P>|z|**
Age						
18-24	*base*					
25-34	0.6	0.4	0.22	0.4	0.6	0.16
35-44	0.5	0.4	0.11	0.2	0.6	0.03
45-54	0.3	0.4	0.00	0.1	0.7	0.00
55-64	0.4	0.4	0.02	0.2	0.6	0.01
65 and older	0.3	0.4	0.00	0.1	0.7	0.00
Gender						
Female	*base*					
Male	1.5	0.2	0.04	1.2	0.3	0.63
Geographic Location						
City	*base*					
Suburb	0.6	0.3	0.08	0.1	0.4	0.00
Small Town/Village	0.2	0.3	0.00	0.1	0.6	0.00
Rural	0.3	0.3	0.00	NA		
Household Size						
1 Person	*base*					
2 Persons	0.8	0.3	0.28	0.9	0.4	0.90
3 Persons	0.8	0.3	0.39	2.0	0.6	0.21
4 or More Persons	0.8	0.3	0.40	0.8	0.6	0.71
Income Quintile						
1 (Lowest)	*base*					
2	1.1	0.4	0.84	0.1	0.5	0.00
3	0.7	0.4	0.40	0.1	0.6	0.00
4	0.5	0.4	0.13	0.1	0.7	0.00
5 (Highest)	1.4	0.4	0.41	0.2	0.6	0.02
Modal Orientation						
Alternative Oriented	*base*					
Car Tolerant	0.2	0.3	0.00	0.0	0.5	0.00
Car Oriented	0.1	0.3	0.00	0.0	0.5	0.00
Year						
2012	*base*					
2018	1.3	0.2	0.13	1.3	0.3	0.51
Constant	30.9	0.5	0.00	400.1	0.7	0.00
Total Observations: 750; Pseudo R2: 0.361; Proportional Reduction in Error: 0.246						

The regression models from **Table 15** and **Table 16** may be used to generate predicted probabilities for the outcomes. **Table 16** presents predicted probabilities for the household vehicle and mode use outcomes based on the modal orientation clusters, holding the additional independent variables at their sample means. For example, the household vehicle model predicts those in the Alternative Oriented cluster have a 2% probability of owning no vehicle, compared to a 1% probability for the Car Tolerant and Car Oriented clusters. Meanwhile, the mode use model predicts those in the Alternative Oriented cluster have only a 9% probability of being a regular driver who does not at least occasionally use transit, biking, or walking, compared to a 38% probability for the Car Tolerant cluster and a 50% probability for the Car Oriented cluster.

Table 17 Predicted Probabilities for the Household Vehicle and Mode Use Outcomes Based on Modal Orientation (Income, Household Size, Geographic Location, and Year at Means)

	Household Vehicles Sample			***Mode Use Sample***			
	Alternative Oriented	Car Tolerant	Car Oriented		Alternative Oriented	Car Tolerant	Car Oriented
Household Vehicles				***Mode Use***			
0 Vehicles	2%	1%	1%	Regular Driver - No Occasional Transit, Bike, Walk	9%	38%	50%
1 Vehicle	47%	30%	23%	Regular Driver - Occasional Transit, Bike, and/or Walk	85%	62%	49%
2 Vehicles	47%	61%	66%	Regular Transit, Bike, and/or Walk	6%	0.2%	0.7%
3 or More Vehicles	4%	8%	11%				
Pooled Cross Sections (2000, 2006, 2012, 2018) Calibration Weights Applied N=1,582				***Pooled Cross Sections (2012, 2018) Calibration Weights Applied N=750***			

The overall predictive capacity of the two models may be assessed in relation to the summary statistics presented in **Table 12**. To do this, the predicted probabilities in **Table 17** are combined with the sample proportions for each model orientation to arrive at predicted probabilities for the outcomes.

Table 18 Comparison of Sample Distributions and Predicted Probabilities for the Household Vehicle and Mode Use Outcomes

Variable	**Sample**	**Predicted**	**Variable**	**Sample**	**Predicted**
Household Vehicles			***Mode Use***		
0 Vehicles	5%	1%	Regular Driver - No Occasional Transit, Bike, Walk	32%	33%
1 Vehicle	34%	32%	Regular Driver - Occasional Transit, Bike, and/or Walk	51%	66%
2 Vehicles	43%	58%	Regular Transit, Bike, and/or Walk	17%	2%
3 or More Vehicles	18%	7%			

A comparison of these predicted probabilities to the summary statistics (**Table 18**) indicates the ordered logistic regression model for household vehicles under-predicts the zero-vehicle and three or more vehicle outcomes and over-predicts the two-vehicle outcome. Meanwhile, the multinomial logistic regression model for mode use over-predicts the Regular Driver – Occasional Transit, Biking, and/or Walk outcome and severely (2% predicted compared to 17% in the sample) the Regular Transit, Biking, or Walk outcome. Error in the prediction of rarer events is reasonably expected.

Discussion

The results presented for household vehicle ownership, mode use, and commuter benefit use in **Table 12** through **Table 17** and **Figure 6** support the findings in prior segmentation literature, summarized in **Table 11**, that modal orientations are significantly associated with travel behavior even after controlling for other traditional measures. Compared to the Alternative Oriented modal orientation, those in the Car Tolerant and Car Oriented clusters are likely to own more vehicles, less likely to rely on transit, biking, or walking as a main mode, and make use of parking commuter benefits at a higher rate and transit commuter benefits at a lower rate.

Although the uniqueness of survey instruments and variation in study areas does not allow for direct comparisons, in general the univariate distribution of the modal orientations in the household vehicle and mode use samples are reasonable compared to those presented in other studies. In the present study, the largest of the three segments is the Car Tolerant, representing about half of all adults, while the other half is split between the Alternative Oriented (about 30%) and Car Oriented (about 20%). For example, Anable (2005) segmented into six groups, with Aspiring Environmentalists (18%), Car-less Crusaders (4%) and Reluctant Riders (3%) together comprising 25% of the sample, Die Hard Drivers comprising 19%, and Malcontented Motorists and Complacent Car Addicts together comprising 56%.

In terms of the additional explanatory variables included as controls, the lower odds for household vehicle ownership among those age 25-34 and 35-44 compared to those age 18-24 is somewhat unexpected, as there has been some attention on lower levels of auto reliance (in terms of measures such as licensure) among younger age cohorts. The increase in odds of owning more household vehicles in the 2012 and 2018 survey years compared to the base in 2000 is also somewhat surprising, given the lasting effects of the Great Recession economic downturn. Also unexpected is the lack of differing odds in mode use by household size, especially with regard to the likelihood of relying on transit, biking, or walking as a main mode. Larger families may be expected to have more complex travel patterns (especially with regard to escort duties for youth or elderly family members) and therefore find use of alternatives more challenging; however, the results suggest mode use does not significantly differ across the household size categories. Most of the findings for geographic location and income are wholly in line with prior travel behavior research. This study confirms the wealth of scholarship suggesting income is a strong predictor of household vehicle ownership, and density is associated with fewer vehicles and more use of alternative modes.

Chapter 4: Telecommunications

Lead Author: Jonathan Fisher

This chapter focuses on the analysis of four telecommunications outcomes (telework availability, interest, and offer/use, as well as reductions in trips due to the internet) in relation to modal orientation, and is organized into three sections: a review of prior research, a presentation of results, and a discussion of the findings.

Literature Review

We reviewed recent findings and ongoing debates in the telecommunications literature, with a particular focus on telecommuting. Telecommuting is a broad and complex phenomenon lacking a single agreed-upon definition, but generally involving information and communications technology (ICT) to perform essential work duties away from the normal place of work (Choo, Mokhtarian et al. 2002). There are two main forms of telecommuting: work performed by salaried workers at home or in another location outside of the main office, and work performed by home-based business owners (Mokhtarian, Salomon et al. 2005). Some intentionally exclude the latter from their definition as it does not include many of the characteristics associated with telecommuting (i.e., a reduction in travel and a deviation from standard home-to-office commute patterns). The survey instruments utilized for the present study do not specify the operationalization of the telecommuting construct; as a result, we adhere to an inclusive definition.

Research on telecommuting as an alternative to traditional commute modes began in the 1970s, when the term “telework” was coined by Nilles (1975), and grew in the 1990s as advances in ICT became widespread. The remainder of this review follows the availability of data available for the present project: 1) offer and use of telecommuting; 2) desire to telecommute; 3) availability of telecommuting; and 4) trip reductions due to the Internet. **Table 18** provides a summary of key studies and relevant findings. The present study contributes to this literature by analyzing multiple telecommunications measures, focusing on a small urban area, and utilizing the segmentation approach (which has not been a major focus in the telecommunications literature to date).

Offer and Use of Telecommuting

The number of telecommuters and frequency of telecommuting vary based on measurement approaches. The American Community Survey (ACS) reports that 5.3% of U.S. adult workers worked from home at least once per week in 2018, a 1% increase from 2010 (U.S. Census Bureau 2018). However, when extending the definition to working at home at least once per *month*, the National Household Travel Survey indicates the share of telecommuters in 2010 was 8% (Jin and Wu 2011). Compared to traditional workers, telecommuters are more likely to be male, have long commute distances, and have higher levels of income (Bailey and Kurland 2002, Jin and Wu 2011, Sener and Bhat 2011). Full-time workers are less likely to telecommute compared to part-time workers, and workers living in areas with high levels of regional accessibility also tend to telecommute less (Tang, Mokhtarian et al. 2011). However, Popuri and Bhat (2003) reveal that, while men are more likely than women to telecommute on average, the presence of children negates this effect. Work-related factors such as job suitability and manager's willingness are always significant when included in studies (Bailey and Kurland 2002, Mokhtarian and Grossman 2020).

The employer offer to telecommute is a prerequisite for telecommuting use. Not all those who are offered telecommuting benefits choose to use them but offer and use are nonetheless closely related. Employers may offer telecommuting to their employees to lower real estate costs, comply with the Americans with Disability Act, and save resources by hiring remote contractors who may not receive benefits (Bailey and Kurland 2002). As Singh, Paleti et al. (2013) note, only a handful of studies to date have examined both the demand-side (use) and supply-side (offer) aspects of telecommuting. Further research into how these two factors interact should be a future priority.

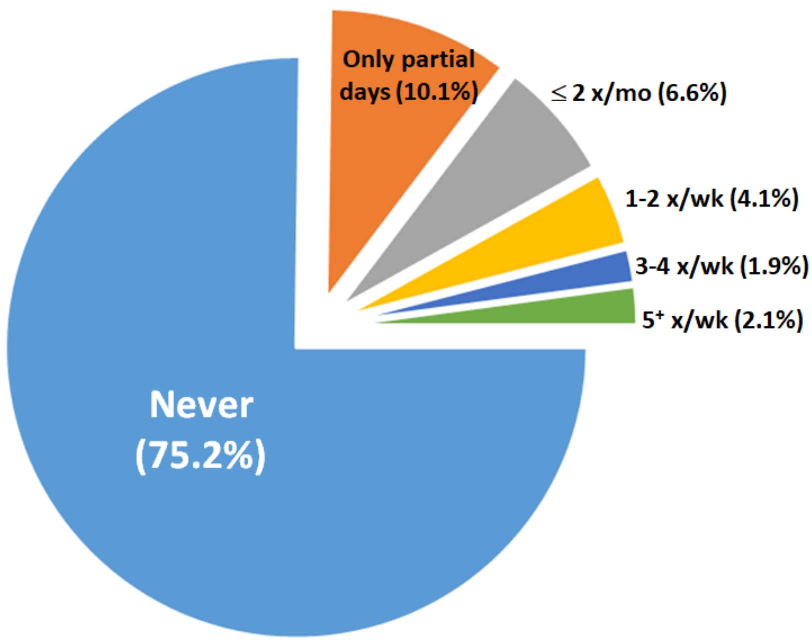

Figure 9 Telecommuting Rates for 2017-2018
Note: Adapted from the presentation by Mokhtarian and Grossman (2020) of data from the 2017-2018 American Time Use Survey.

Desire to Telecommute

More recently, researchers have begun investigating the choice of whether to telecommute when given the option, and have found, as expected, variation between stated and revealed preferences. For instance, Mokhtarian and Salomon (1996) found that only 37% of respondents who reported both desiring and having the option to work at home actually chose to do so, as discussed recently by Mokhtarian and Grossman (2020).

Factors influencing the choice to telecommute may be grouped into two categories: demand factors (workers' desire to telecommute) and supply factors (companies' desire for their employees to telecommute). Among workers, marital status, part-time work status, access to technology and the internet, and living in rural areas are all positively correlated with having a desire to telecommute (Popuri and Bhat 2003, Singh, Paleti et al. 2013). Jobs that require face-to-face interaction make workers less likely to want to telecommute, while income, age, and reducing commute time have mixed or insignificant effects (Bailey and Kurland 2002, Popuri and Bhat 2003, Singh, Paleti et al. 2013). Significant supply factors include manager's trust and willingness, large firm size, and being a private rather than a public company (Bailey and Kurland 2002, Popuri and Bhat 2003).

New research into the desire to telecommute has emerged during the current COVID-19 pandemic. With unprecedented numbers of workers working at home for extended periods of time, many are expressing interest in continuing to telecommute once workplaces reopen. Studies by IBM and Morning Consult report that around 75% of Americans would like to work from home at least part-time after COVID work restrictions have ended while about a third would like to work from home full-time (Mokhtarian and Grossman 2020). The impacts of the COVID-19 pandemic on telecommuting specifically, and travel behavior more generally, will likely receive ongoing scholarly attention; preliminary results suggest recent exposure to telecommuting has increased the desire among American workers to telework in the future.

Availability of Telecommuting

Given that the desire to telecommute among American workers is relatively high while actual rates remain low, it is reasonable to attribute this gap to a lack of availability of telecommuting options, a claim that is supported by the literature. In their study of telecommuting choice, Mokhtarian and Salomon (1996) identify a "preferred impossible alternative" scenario where the alternative (telecommuting) exists in the set of preferences but not in the set of choices. In other words, more workers want to telecommute than can.

Rates on telecommuting availability vary by source and how they are measured. Based solely on job category, between 37% and 56% of workers may be able to telecommute; however, based on allowance or eligibility, the figures range from 7% to 27% (Mokhtarian and Grossman 2020). Identifying telecommuting availability by a worker's job type may be difficult because every job has unique characteristics. Bailey and Kurland (2002) indicate that individuals often perceive their job to be unsuitable because of their particular duties, even if it is within a category of jobs that lends itself to telecommuting. Other factors that constrain availability include lack of awareness, manager unwillingness, high neighborhood housing density, and working for the government (Mokhtarian and Salomon 1996, Singh, Paleti et al. 2013). Meanwhile, middle age, high income and education levels, full-time employment status, internet use, high commute length, and working in professional and technical occupations are all positive indicators of the availability of telecommuting (Sener and Bhat 2011, Singh, Paleti et al. 2013).

Trip Reduction Due to the Internet

Innovations in ICT have long been heralded for their propensity to decrease trips taken and increase connectivity. Along with telecommuting, use of the internet for online shopping and education also offer potential means of reducing overall travel.

As one would expect, telecommuting significantly reduces commute-related travel (Choo, Mokhtarian et al. 2002, Popuri and Bhat 2003, Kwan, Dijst et al. 2007). However, when measuring the effects on total travel, the reduction is diminished. In a comprehensive national-level study, Choo et al. (2002) analyzed total vehicle miles traveled (VMT) across the U.S. and found a 2% reduction in total VMT attributable to telecommuting. This may relate to a 'rebound effect' whereby reductions in travel from telecommuting are offset by other types of travel. Trips to satellite offices, errands previously linked to commute trip-chains, travel in new leisure time, and travel by household members with newly available vehicles may all offset telecommuting travel reductions (Popuri and Bhat 2003). Thus, while telecommuting greatly reduces work-related travel, when measuring total travel, the effect is diminished.

Other internet-related activities such as online shopping and online education have also been found to result in reductions in travel. Corpus and Peachman (2003) concluded that around 15% of internet transactions directly substitute for a trip, while Tonn and Hemrick (2004) found that 40% of respondents replaced an in-person trip with internet use in a two-week period. Both studies indicate that trips to work, stores, and banks are most easily used for trip substitution, while trips to schools, grocery stores, and visits to relatives remain mostly unchanged. While numerous studies have shown that the internet can create new trips due to increased information about shopping discounts and recreational and social opportunities (Corpuz and Peachman 2003, Popuri and Bhat 2003), in general there is consensus that the net effect of internet use is an overall reduction in travel. For instance, compared to those who shop in person, online shoppers tend to make shorter but more frequent trips and often link trips together, which can reduce total travel amounts (Farag, Krizek et al. 2006, Kwan, Dijst et al. 2007). Additionally, Tonn and Hemrick found that internet use replaces a trip twice as often as it generates one (2004).

As with the 'rebound effect' found with telecommuting, the reduced travel associated with online shopping may actually generate an increase in emissions due to the displacement of individual vehicle trips from passenger cars with trips by heavier delivery trucks. As a result, online shopping may reduce total VMT but increase greenhouse gas emissions (Jaller 2020, Jaller and Pahwa 2020). Trip reductions due to online learning have received less attention than online shopping (see, however, Bartley and Golek 2004), but this may change in light of the COVID-19 pandemic's dramatic impact on education at all levels.

Table 19 Overview of Recent Telecommunications Literature

Study	Data Source (Study Area)	Study Question(s)/ Key Variables	Key Findings
Offer and Use of Telecommuting			
Bailey and Kurland (2002)	Review (United States)	Who teleworks, why, and what happens when they do?	Two main teleworker profiles: male professional & female clerical workers Positive predictors of use: job suitability, manager willingness, technology access Reasons to offer: savings on real estate, overhead costs, and employee benefits; ADA compliance
Jin and Wu (2011)	1995 NPTS; 2001, 2009 NHTS (United States)	Work-related, individual, household, travel, and land use factors of telecommuting use and frequency	Positive predictors of use: multiple jobs, high commute length, older age, male, White or Asian, high income, families with children, living in urban areas, using non-car transportation alternatives Positive predictors of frequency: part-time work status, young families with children
Mokhtarian (2020)	Review (United States)	How many people telework, and how often?	Reported telework rates, pre-COVID: 5.3% (ACS), 8% (American Time Use Survey), 12% (NHTS) Reported telework rates, during COVID: 40% (Pew), 62% (Gallup)
Sener and Bhat (2010)	2007-08 Chicago Regional Household Travel Inventory (Chicago)	Individual, household, work-related, and travel factors of propensity to telecommute	Positive predictors: male, flexible work schedule, jobs in communications and service industries, families with children, high household income, high commute distance, pro-bicycling and pro-transit attitudes, vehicle availability Negative predictors: younger age, jobs in government
Tang et al. (2011)	Mailed household survey (Northern California)	Travel, built environment, neighborhood, and socio-demographic factors of the decision to work at home	Positive predictors: high income and education, pro-bicycling and pro-transit attitudes, high commute time, number of eat-out businesses within 400m Negative predictors: high level of regional accessibility, full-time work status
Desire to Telecommute			
Bailey and Kurland (2002)	Review (United States)	Why do people telework?	Positive supply factors: manager’s trust, large firm size Negative supply factors: low manager interest, difficulty of coordination Insignificant factors: commute reduction
Mokhtarian (2020)	Review (United States)	How many people say they want to telework?	37% of workers who could and wanted to telework did (Mokhtarian and Salomon, 1996) Of those who worked at home during COVID:

Study	Data Source (Study Area)	Study Question(s)/ Key Variables	Key Findings
			59% want to continue (Gallup); 54% want to continue full-time and 75% part-time (IBM)
Popuri and Bhat (2003)	1997-98 Regional Transportation Household Interview Survey (New York City)	Individual, household, and work-related factors of the choice to telecommute	Positive demand factors: marital status, high education, number of household vehicles, high household income, access to technology, working for a private company, part-time work status, no free parking at workplace Negative demand factors: jobs that require face-to-face interaction Insignificant factors: gender, age
Singh et al. (2012)	2009 NHTS (San Francisco Bay)	Individual, household, work-related, and built environment influences on telecommuting option, choice, and frequency	Positive demand factors: female, Internet access, part-time work status, high commute length, presence of young children, living in rural areas and sparsely populated neighborhoods, living closer to non-work and leisure activities Insignificant factors: income
Availability of Telecommuting			
Mokhtarian (2020)	Review (United States)	How many people can work from home?	Based on job: 56% (Global Analytics, 2020), 40% (Pew, 2020), 37% (Dingel and Neiman, 2020) Based on allowance/eligibility: 29% (BLS, 2019a), 18% (NHTS, 2017). 7% (BLS, 2019b)
Mokhtarian and Salomon (1996)	Survey of San Diego employees (San Diego, California)	Modeling the choice of telecommuting	Constraints: lack of awareness, job unsuitability, manager unwillingness
Sener and Bhat (2010)	2007-08 Chicago Regional Household Travel Inventory (Chicago)	Individual, household, work-related, and travel factors of propensity to telecommute	Positive predictors of availability: full-time employment status (>30 hours per week)
Singh et al. (2012)	2009 NHTS (San Francisco Bay)	Individual, household, work-related, and built environment influences on telecommuting option, choice, and frequency	Positive predictors of availability: male, middle age, high income and education, Internet use, using non-car transportation alternatives, full-time work status, professional and technical occupations, high commute length, presence of young children, living in urban areas Negative predictors: high neighborhood density Insignificant predictors: marital status, living closer to non-work and leisure activities
Trip Reduction Due to the Internet			
Bartley and	Theoretical cost	Cost effectiveness	Online education and training increase

Study	Data Source (Study Area)	Study Question(s)/ Key Variables	Key Findings
Golek (2004)	matrix analysis (United States)	of online and face-to-face instruction	accessibility by removing the need for travel and result in travel cost reductions
Choo et al. (2002)	Aggregate study of US Census and Government data (United States)	Impacts of telecommuting on vehicle miles traveled (VMT)	Telecommuting significantly decreases VMT (90% confidence) Reduction in total VMT due to telecommuting is around 2%
Corpuz and Peachman (2003)	Sydney Household Travel Survey (Sydney, Australia)	Measuring impacts of internet usage on travel behavior	15% of internet transactions directly substitute for a trip Most internet usage has no effect on travel
Jaller and Pahwa (2020)	2016 American Time Use Survey, 2010 Census (Dallas and San Francisco)	Individual shopping behavior influence on VMT and emissions	Online shopping reduces total VMT by 7.2%-87.6% Nitrous Oxide emissions rise around 24% due to increased delivery truck mileage
Kwan et al. (2007)	Review (Global)	Interaction between ICT and travel behavior	Telecommuters reduce commute-related travel but increase non-work travel Online shopping increases chained shopping trips but decreases overall travel distance
Popuri and Bhat (2003)	1997/98 Regional Transportation Household Interview Survey (New York City)	Individual, household, and work-related influences on the choice to telecommute	Travel reduction: substituting for commute trips Travel generation: trips to satellite office, travel previously linked to work commute, new leisure time travel, travel of other household members due to new vehicle availability
Tonn and Hemrick (2002)	Web survey of internet users (Knoxville, TN)	Impacts of internet use and individual demographic factors on trip-making behavior	40% of respondents used the internet to replace a trip Trip replacement was 2x as common as trip generation Internet use led to 8% reduction in overall trips

Results

Table 20 presents the distributions of the four telecommunications outcomes by survey year and modal orientation, while **Figure 10** presents the share of CC employed residents offered and using teleworking benefits by modal orientation and survey year (similar to the information presented in **Figure 8** for employer-based car parking and transit benefits). Notably, all four measures increased over time, except for a slight decline in telework availability between 2000 and 2006. Telework availability increased by over 40% between 2000 and 2018, with just over a third of respondents having a telework-friendly job in 2018. Telework interest is quite high, at 93% in 2006, although the sample sizes are small in both years for which this information was collected. The share of workers offered telecommuting benefits increased from 24% in 2012 to 35% in 2018, tracking closely the telework availability rates, while usage also showed a substantial increase. Finally, trip reductions due to the internet have almost doubled since 2000, with nearly three quarters of respondents in 2018 reporting this outcome.

Telework availability, offer, and use do not differ significantly by modal orientation. However, telework interest does vary significantly by modal orientation, with 77% of the Car Oriented cluster interested compared to 90% and 94% for the Alternative Oriented and Car Tolerant clusters, respectively. The share of respondents reporting trip reductions due to the internet also differs significantly by modal orientation, with 57% of the Car Oriented Cluster compared to 61% and 65% for the Alternative Oriented and Car Tolerant clusters, respectively.

Table 20 Distribution of the Telecommunication Outcomes by Survey Year and Modal Orientation

		2000	**2006**	**2012**	**2018**	**Alternative Oriented**	**Car Tolerant**	**Car Oriented**	**Pooled**
Telework Availability	Total (N)	234	430	363	327	357	631	295	1,354
	No	76%	81%	76%	66%	73%	75%	75%	75%
	Yes	24%	19%	24%	34%	27%	25%	25%	25%
		F Test: p=0.000				F Test: p=0.655			
Telework Interest	Total (N)	63	90			47	70	25	153
	No	12%	7%			10%	6%	23%	9%
	Yes	88%	93%			90%	94%	77%	91%
		T-test p-value=0.226				F Test: p=0.047			
Telework Offer & Use	Total (N)			304	285	145	289	136	589
	Not Offered			76%	65%	66%	74%	69%	71%
	Offered & Not Used			8%	7%	8%	7%	7%	8%
	Offered & Used			15%	28%	26%	19%	24%	21%
				F Test: p=0.000		F Test: p=0.158			
Trip Reductions Due to the Internet	Total (N)	243	491	433	410	414	735	345	1,577
	No	60%	43%	35%	26%	39%	35%	43%	39%
	Yes	40%	57%	65%	74%	61%	65%	57%	61%
		F Test: p=0.000				F Test: p=0.063			

Note: Tabulations for telework availability, interest, and offer tabulations limited to employed CC residents. Calibration weights applied.

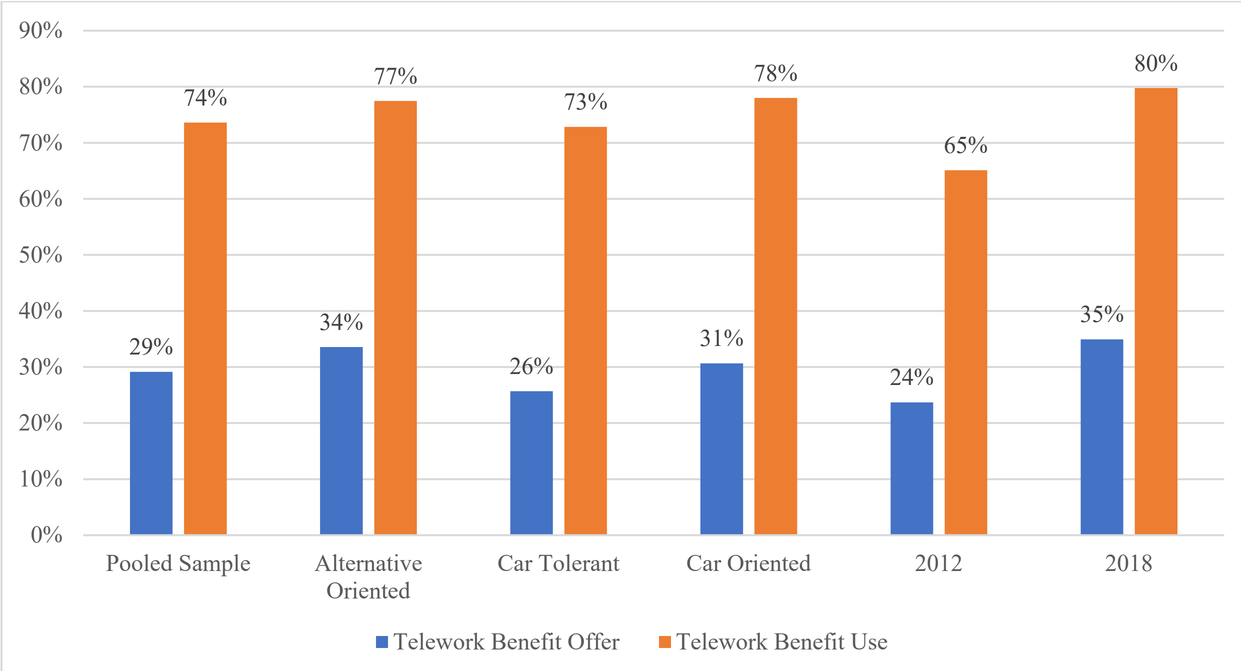

Figure 10 Share of Chittenden County Employed Residents Offered and Using Teleworking Benefits by Modal Orientation and Survey Year
Note: Tabulations are limited to employed CC residents.

Because of the similarity in the information collected in the telework availability and offer questions, and the small sample size for telework interest, we chose to proceed with multivariable regression analysis for only two of the telecommunications outcomes: telework availability, and trip reductions due to the internet. While both of these outcomes were collected throughout the entire survey series, the regression results presented below only pooled 2006, 2012, 2018 survey responses, as education (not collected in 2000) was included in the models.

Table 21 presents the summary statistics for the samples used below in the telework availability and trip reduction logistic regression models. The 65+ age group is underrepresented in the telework availability sample, with just 4.7% falling in this group compared to an average for CC of 14.25% from 2000-2018 Census data. The 35-64 age group is similarly overrepresented, likely making up for the lack of older respondents. Both samples show higher education rates than the CC average as well. Just under half of respondents live in suburban areas in both samples, while around 30% live in cities and 15% each in small towns/villages and rural areas. The Car Tolerant cluster is the largest, comprising above 50% of respondents in both samples, followed by the Alternative Oriented and Car Oriented clusters.

Table 21 Summary Statistics for the Telework Availability and Trip Reduction Samples

Telework Availability					Trip Reduction Due to Internet				
Variable	**Obs**	**Mean**	**Min**	**Max**	**Variable**	**Obs**	**Mean**	**Min**	**Max**
Telework Availability					***Trip Reduction Due to Internet***				
No	1,043	75%	0	1	No	1,282	35%	0	1
Yes	1,043	26%	0	1	Yes	1,282	65%	0	1
Age									
18-34 Years	1,043	35%	0	1	18-34 Years	1,282	35%	0	1
35-64 Years	1,043	60%	0	1	35-64 Years	1,282	50%	0	1
65+ Years	1,043	5%	0	1	65+ Years	1,282	15%	0	1
Education									
High School Diploma or Lower	1,043	7%	0	1	High School Diploma or Lower	1,282	10%	0	1
Some College or Associate's Degree	1,043	22%	0	1	Some College or Associate's Degree	1,282	24%	0	1
Bachelor's Degree or Higher	1,043	71%	0	1	Bachelor's Degree or Higher	1,282	66%	0	1
Gender									
Female	1,043	50%	0	1	Female	1,282	50%	0	1
Male	1,043	51%	0	1	Male	1,282	50%	0	1
Geographic Location									
City	1,043	28%	0	1	City	1,282	29%	0	1
Suburb	1,043	44%	0	1	Suburb	1,282	44%	0	1
Small Town/Village	1,043	14%	0	1	Small Town/Village	1,282	14%	0	1
Rural	1,043	14%	0	1	Rural	1,282	13%	0	1
Income Quintile									
1 (Lowest)	1,043	11%	0	1	1 (Lowest)	1,282	19%	0	1
2	1,043	20%	0	1	2	1,282	19%	0	1
3	1,043	22%	0	1	3	1,282	20%	0	1
4	1,043	17%	0	1	4	1,282	14%	0	1
5 (Highest)	1,043	30%	0	1	5 (Highest)	1,282	27%	0	1
Modal Orientation									
Alternative Oriented	1,043	27%	0	1	Alternative Oriented	1,282	29%	0	1
Car Tolerant	1,043	51%	0	1	Car Tolerant	1,282	50%	0	1
Car Oriented	1,043	22%	0	1	Car Oriented	1,282	20%	0	1
Year									
2006	1,043	37%	0	1	2006	1,282	37%	0	1
2012	1,043	33%	0	1	2012	1,282	33%	0	1
2018	1,043	30%	0	1	2018	1,282	30%	0	1
Employment Sector					***Pooled Cross Sections (2006, 2012, 2018) Calibration Weights Applied***				
Clerical/Secretarial	1,043	6%	0	1					
Executive/Managerial	1,043	17%	0	1					

Telework Availability					Trip Reduction Due to Internet				
Variable	**Obs**	**Mean**	**Min**	**Max**	**Variable**	**Obs**	**Mean**	**Min**	**Max**
Professional/Technical	1,043	52%	0	1					
Sales/Buyer	1,043	2%	0	1					
Teacher/Professor	1,043	10%	0	1					
Retail/Service	1,043	10%	0	1					
Mechanical/Maintenance/ Manufacturing	1,043	4%	0	1					
Employment Status									
Full-time	1,043	86%	0	1					
Part-time	1,043	14%	0	1					
Pooled Cross Sections (2006, 2012, 2018) Calibration Weights Applied									

Table 22 presents the results of the binary logistic regression model for the likelihood of having telework availability. Results are in the form of odds ratios (OR): factors with an OR above 1 increase the odds of telecommuting availability compared to the base category, while those with an OR below 1 lower the odds. As expected, the odds of being able to telecommute increases with education. Those above the age of 65 are less likely to have the option (OR=0.484), although there is little difference between the 18-34 and 35-64 age groups. Once again, employment sector has an effect, with those employed in executive/managerial (OR=1.762), professional/technical (OR=1.97), and sales/buyer (OR=4.207) positions showing higher rates of availability, though the first group's test statistic just misses the threshold for significance. Meanwhile, those in the retail/service (OR=0.347) and mechanical/maintenance/manufacturing (OR=0.344) sectors have the lowest availability odds, though again the second group's result is not significant at the 0.1 level. Part-time workers are about 1.8 times more likely to be able to telework than full-time workers, a result that is consistent with the literature. Though income displays a strong positive correlation with teleworking availability in the bivariate tabulations and in much of the literature, the effects in this model are both small and not significant. Gender and modal orientation cluster also fail to meet the significance threshold, but their theoretical importance is enough to merit their inclusion in the regression. Living in a rural or suburban area, however, plays a significant role: rural workers are 1.932 times more likely and suburban workers 1.376 times more likely to have telecommuting availability than city workers. Finally, the year dummy variable is both greater than 1 and significant, which means that holding everything else constant, telework availability increased across survey years.

Table 23 presents the binary logistic regression results for the likelihood of reducing trips due to the internet, with the coefficients presented as odds ratios. The model suggests that older people are less likely to make trip reductions due to the internet, especially those at or above age 65 (OR=0.42). Males are 1.223 times more likely to use the internet to substitute for trips than females, though this result is slightly above the significance threshold ($p<0.103$). Once again, education has a highly significant positive effect on this behavior, which increases with each additional level of educational attainment. The same effect is true for income, with those in the highest quintile (OR=3.214) more than 3 times as likely to reduce their trips with internet use than those in the lowest quintile. Trip reduction also varies according to modal orientation.

Compared to the Car Oriented group, the Alternative Oriented (OR=1.502) and Car Tolerant (OR=1.824) groups both show higher propensities to change their behavior. The odds do not significantly differ by geographic location. Finally, the year dummy variable is positive and highly significant in this model, indicating that trip reduction due to internet use has increased over time.

Table 22 Binary Logistic Regression Results (Likelihood of Telecommuting Availability)

Outcome: Probability of Telecommuting Availability						
	Odds Ratio	**Std. Err.**	**z**	**P>|z|**	**[95% Conf.**	**Interval]**
Age						
18-34 Years	*base*					
35-64 Years	1.0	0.2	-0.3	0.78	0.7	1.4
65+ Years	0.5	0.2	-1.9	0.05	0.2	1.0
Education						
High School Diploma or Less	*base*					
Some College or Associate Degree	1.7	0.8	1.2	0.25	0.7	4.5
Bachelor's Degree or Higher	2.7	1.3	2.2	0.03	1.1	6.8
Employment Status						
Full-time	*base*					
Part-time	1.8	0.4	2.4	0.02	1.1	2.9
Employment Sector						
Clerical/Secretarial	*base*					
Executive/Managerial	1.8	0.6	1.5	0.12	0.9	3.6
Professional/Technical	2.0	0.7	2	0.05	1.0	3.8
Sales/Buyer	4.2	2.2	2.7	0.01	1.5	12.0
Teacher/Professor	0.6	0.3	-1.1	0.25	0.3	1.4
Retail/Service	0.3	0.2	-1.9	0.05	0.1	1.0
Mechanical/Maintenance/ Manufacturing	0.3	0.3	-1.3	0.20	0.1	1.7
Gender						
Female	*base*					
Male	1.3	0.2	1.5	0.13	0.9	1.7
Geographic Location						
City	*base*					
Suburb	1.4	0.3	1.7	0.09	1.0	2.0
Small Town/Village	1.1	0.3	0.5	0.61	0.7	1.9
Rural	1.9	0.5	2.6	0.01	1.2	3.2
Income Quintile						
1 (Lowest)	*base*					
2	0.7	0.3	-0.9	0.37	0.3	1.5
3	0.7	0.3	-0.8	0.41	0.3	1.5
4	1.1	0.4	0.2	0.84	0.5	2.3
5 (Highest)	1.1	0.4	0.3	0.76	0.5	2.4
Modal Orientation						
Car Oriented	*base*					
Alternative Oriented	1.3	0.3	1	0.30	0.8	1.9
Car Tolerant	0.8	0.2	-1	0.32	0.6	1.2
Year						
2006	*base*					
2012	1.6	0.3	2.4	0.02	1.1	2.3
2018	2.1	0.4	4.2	0.00	1.5	3.1
Total Observations: 1057; Pseudo R2: 0.107; Proportional Reduction in Error: 0.021						

Table 23 Binary Logistic Regression Results (Likelihood of Reducing Trips due to the Internet)

Outcome: Probability of Reducing Trips Made by Using the Internet						
	Odds Ratio	**Std. Err.**	**z**	**P>|z|**	**[95% Conf.**	**Interval]**
Age						
18-34 Years	*base*					
35-64 Years	0.8	0.1	-1.2	0.22	0.6	1.1
65+ Years	0.4	0.1	-4.1	0.00	0.3	0.6
Education						
High School Diploma or Less	*base*					
Some College or Associate Degree	1.8	0.4	2.4	0.02	1.1	2.8
Bachelor's Degree or Higher	2.2	0.5	3.6	0.00	1.4	3.4
Gender						
Female	*base*					
Male	1.2	0.2	1.6	0.10	1.0	1.6
Geographic Location						
City	*base*					
Suburb	1.3	0.2	1.6	0.10	1.0	1.7
Small Town/Village	1.2	0.3	1	0.30	0.8	1.9
Rural	1.3	0.3	1.2	0.22	0.9	2.0
Income Quintile						
1 (Lowest)	*base*					
2	1.7	0.4	2.2	0.03	1.0	2.6
3	2.0	0.4	3	0.00	1.3	3.1
4	3.1	0.8	4.6	0.00	1.9	5.0
5 (Highest)	3.2	0.8	4.9	0.00	2.0	5.1
Modal Orientation						
Car Oriented	*base*					
Alternative Oriented	1.5	0.3	2.2	0.03	1.1	2.1
Car Tolerant	1.8	0.3	3.8	0.00	1.3	2.5
Year						
2006	*base*					
2012	1.3	0.2	1.9	0.06	1.0	1.8
2018	2.6	0.4	5.8	0.00	1.9	3.6
Total Observations: 1309, Pseudo R2: 0.092, Proportional Reduction in Error: 0.123						

Discussion

The results presented for telework availability, interest, and offer, along with trip reductions due to the internet in **Table 20** through **Table 23** generally support the findings in prior telecommunications literature. The increase in all four telecommunications outcomes over time (**Table 20**) may reflect ongoing advances in ICT, greater familiarity with and acceptance of telecommunications, and a shift in traditional work and travel behavior. Figures for telework availability range from 22.1% in 2000 to 33.9% in 2018 and roughly align with the estimates recently presented by Mokhtarian and Grossman (2020). Telework availability and telework offer rates, which closely track for the two survey years in which both questions were asked, may be an indicator of managerial support, a strong determinant of telecommuting (Bailey and Kurland 2002, Popuri and Bhat 2003). The high telework desire rates (80% in 2000, 94.9% in 2006) were based on a question only posed to those who reported having the type of job that could be done at home, and are therefore likely to be higher than the rates for the general working population; workers who wish to telework may be expected to seek out a job that would allow them to do so (Sener and Bhat 2011).

To our knowledge, our analysis offers the first application of traveler segmentation for models of the likelihood of having telework availability and reducing trips due to the internet. The results indicate that telework availability does not differ by modal orientation, but the odds of reducing trips due to the internet are significantly higher for the Alternative Oriented and Car Tolerant clusters compared to the Car Oriented cluster. The difference in significance by modal orientation between these two outcomes may relate to the differing degrees of individual autonomy in these outcomes – with trip reductions more easily implemented than changes in employment conditions.

In terms of additional explanatory variables included as controls, findings in the telecommuting availability and trip reduction models are largely consistent with prior literature. Highlights include significantly lower odds for the oldest age group (65+) for both outcomes (consistent with the finding of lower internet use among older adults in Corpuz and Peachman 2003), higher odds among those with a college degree for both outcomes (as well as those with some college or an Associate's Degree for the trip reduction outcome only), and no difference in odds by income for telework availability but a significantly positive association of income with the trip reduction outcome (consistent with the positive association between income and internet access and use in Corpuz and Peachman 2003). The education findings may reflect value differences in terms of sustainability and environmentalism or increased technological ability associated with higher education levels. The odds of having telework availability differ significantly for several employment sector categories. Compared to the Clerical/Secretarial base category, the odds are significantly higher for Professional/Technical and Sales/Buyer workers, but lower for Retail/Service workers; they do not differ significantly for those in Executive/Managerial, Teacher/Professor, or Mechanical/Maintenance/Manufacturing positions. These results are generally consistent with the expectation that positions requiring more face-to-face interaction or utilization of specialized equipment would not easily translate to telework settings (Popuri and Bhat 2003). Compared to city residents, suburban and rural residents are more likely to have the option to telecommute (but not, surprisingly, small town/village residents). Longer commute times and fewer public transit or bike/walk transportation options could increase the likelihood that a worker would request and be granted telework availability (Tang, Mokhtarian et al. 2011).

A few results contrast prior research, including our finding of significantly higher odds of telework availability among part-time workers (in contrast, see Sener and Bhat 2011, Singh, Paleti et al. 2013) and a lack of significance for income in relation to telework availability (in contrast, see Jin and Wu 2011, Singh, Paleti et al. 2013). Gender was also insignificant in both models; no trip purpose information could be linked to the trip reduction outcomes, but we could speculate that gendered patterns in tripmaking could impact this outcome. Studies have found that trips to work, retail outlets, and banks are more easily substituted for than trips to school, grocery stores, or relatives, of which the latter still persistently fall disproportionately to female household members (Corpuz and Peachman 2003, Tonn and Hemrick 2004). Finally, while prior research suggests trip reductions due to the internet would be lowest for urban residents, as their relative proximity to destinations such as restaurants and shopping would lower the incentive to forgo trips (Farag, Krizek et al. 2006), trip reductions did not differ by geographic location in our model. This may relate to the relatively small size of CC's urban area (Burlington and Winooski) or lower levels of congestion compared to the larger study areas in prior research

Chapter 5: Planning Priorities

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This chapter focuses on the analysis of transportation planning priorities (regional spending by category, and support for increasing gas taxes) in relation to modal orientation, and is organized into three sections: a review of prior research, a presentation of results, and a discussion of the findings.

Literature Review

Spending by Category

Our analysis of spending by category focuses on comparing project funding in the CCRPC TIP (Obligated) to the distribution of resources described by the general public in the 2018 survey instrument. We approach this analysis from the perspective of evaluating the degree to which regional transportation planning reflects citizen input and involvement. Federal guidance on citizen participation (Jordan 1976) and its codification into surface transportation authorizations (see discussion of recognition in TEA-21 of essential role of public involvement in accomplishing the the bill's vision in Khisty 2000) reflect a national appreciation of the importance of citizen participation to the planning process. Citizen input may be achieved using a variety of tools and methods, including surveys, workshops, and meetings for the general public, stakeholders, and appointed citizen representatives. A tension may exist between the technocratic expertise of planning professionals and the attitudes and opinions of the general public; ideally, genuine opportunities for impactful citizen input are provided throughout a decision-making process and designed to enact community values such as fairness, inclusion, and efficiency.

In terms of comparable evaluations of public priorities for transportation planning, McCann, Kienitz, and DeLille (2000) reviewed transportation spending trends as well as polls and surveys from across the country and found widespread evidence of a priority among most people for more travel choices. As they summarized: a 1998 study from the Twin Cities, MN, found 88% of residents preferred balanced transportation spending that supported transit; a 1999 study from suburban Washington found a voter preference for transit spending over highways by a factor of three to one; a 1999 study of Detroit found residents, businesses, and employees favored new mass transit rather than highway capacity investments to relieve congestion; and a 2000 study of the San Francisco Bay area found that 76% of respondents considered transit a high priority compared to only 36% for road building.

Relating to the segmentation approach employed in this study, Jordan (1976) noted that responses could enable the grouping of citizens with common views for more effective targeting. To our knowledge, this is the first study to use travel survey data to compare actual regional spending proportions to the preferences of the public being served, and the first to use the lens of traveler segmentation by modal orientations to understand variations in spending priorities.

Gas Taxes

Our analysis of public support for gas tax increases focuses on overall support as well as relative support for increases that go only to highways versus non-highway purposes. The use of motor fuel taxes for non-highway (or non-roadway) purposes has essentially always been controversial. The original federal gas tax accrued in the general fund and was not explicitly restricted to highway or transportation infrastructure spending, but with the establishment of the federal Highway Trust Fund in 1956, federal gas tax revenues were earmarked for roadway spending and the public was assured that the tax revenues would be used exclusively to improve the nation's roads (Puentes and Prince 2003, Weingroff 2013). However, the Federal-Aid Highway Act of 1973 'busted the trust' back open by allowing some Highway Trust Fund revenue to be allocated for rail transit (Weingroff 2013), and the trend continued with the Surface Transportation Act of 1982 allocating a portion of gas tax revenues into the Mass Transit Account for capital projects (Puentes and Prince 2003). In terms of state gas taxes, thirty states do impose restrictions on the use of their revenues for highway purposes, which has the effect of limiting transit investments (Puentes and Prince 2003). Opponents of these restrictions highlight the environmental and equity benefits of non-highway spending and point out that gas tax revenues have not kept up with inflation and do not cover the full cost of roadways. At the federal level, the Highway Trust Fund has received multiple transfers from the General Fund of the Treasury since 2008 to maintain a positive balance. Gas tax increases have typically been avoided by elected officials, who find it challenging to adopt fuel tax rates high enough to generate adequate revenues (Goldman, Corbett et al. 2001); instead, they have often turned to alternative revenue sources, such as sales taxes paid by all citizens, that may have significant unintended consequences for our transportation systems as well as equity (Wachs 2003).

In a long-running survey series, Agrawal and Nixon (2010, 2020) have found that support for a gas tax increase for generic/unspecific transportation purposes (the "base case") has increased from 23% in 2010 to 44% in 2020. They also found higher (compared to the "base case") and increasing levels (over time) of support for gas tax increases linked to revenues spent to reduce local air pollution (30% in 2010 vs. 56% in 2020), reduce global warming (42% in 2010 vs. 61% in 2020), maintain streets, roads, and highways (62% in 2011 vs. 75% in 2020), and reduce accidents and improve safety (56% in 2011 vs. 73% in 2020) (see Table 15 in Agrawal and Nixon 2020). In their most recent survey, 71% of respondents supported spending some gas tax revenue on public transit (Agrawal and Nixon 2020).

Dill and Weinstein (2007) summarize several polls on gas tax increases that suggest a majority of the public does not support them, and indeed support is typically under 40%. They also generated a binary logistic regression model for the likelihood of supporting a gas tax increase (as well as additional revenue options, including flat and variable registration fees) that included sociodemographic measures (age, education, gender, income, race), attitudes (taxes, transportation system, transit spending, and political orientation), and travel behavior (weekly miles driven, status as a transit user). All of the independent variables included in their model for support for gas tax increases were statistically significant (using a threshold of $p<0.1$); specifically, age, education, income, support for focusing transportation spending on transit, a liberal political orientation, and being a transit user were positively associated with support for increasing the gas tax while being female and feeling taxes were too high were negatively associated with support for increasing the gas tax (Dill and Weinstein 2007). The present study builds on this regression analysis and its inclusion of attitudinal measures by incorporating modal orientations.

This study contributes to the literature on support for gas tax increases by utilizing a small urban travel survey series, and by offering an application of traveler segmentation by modal orientation to evaluate increases in gas taxes.

Results

Spending by Category

Figure 11 presents the share of regional transportation spending for highway, transit, and bike/walk projects in relation to public opinion on this spending, as represented by the distribution of points assigned to these categories in the 2018 survey. Across FY 2000 through FY 2018, out of a total of $628,583,410 in spending, the CCRPC TIP (Obligated) included $113,614,383 (18%) for "New Facility/Major Roadway Upgrades" (denoted Highway below), $106,538,483 (17%) for "Transit" (denoted Transit below), and $45,356,932 (7%) for "Bike/Pedestrian" projects (denoted Bike/Walk below) (Chittenden County Regional Planning Commission 2020). In contrast, the survey sample as a whole assigned 8% of points to Highway projects, 11% of points to Transit, and 19% of points to Bike/Walk projects. As expected, the distribution of points among these three spending categories varied across the three modal orientations. Highway projects received only 5% of points from the Alternative Oriented, but 14% from the Car Oriented. Meanwhile, the Alternative Oriented assigned 20% of points to Transit and 28% of points to Bike/Walk projects, while the Car Oriented assigned only 5% of points to Transit and 11% to Bike/Walk projects. The distribution of points for the Car Tolerant group was in between the Alternative Oriented and Car Oriented Group in each case (8% for Highways, 10% for Transit, and 18% for Bike/Walk projects, respectively). Overall, spending in the TIP (Obligated) was higher on Highways (18% versus 8%) and Transit (17% versus 11%) than it was for the general public (as represented by the survey sample as a whole), but lower for Bike/Walk projects (7% versus 19%).

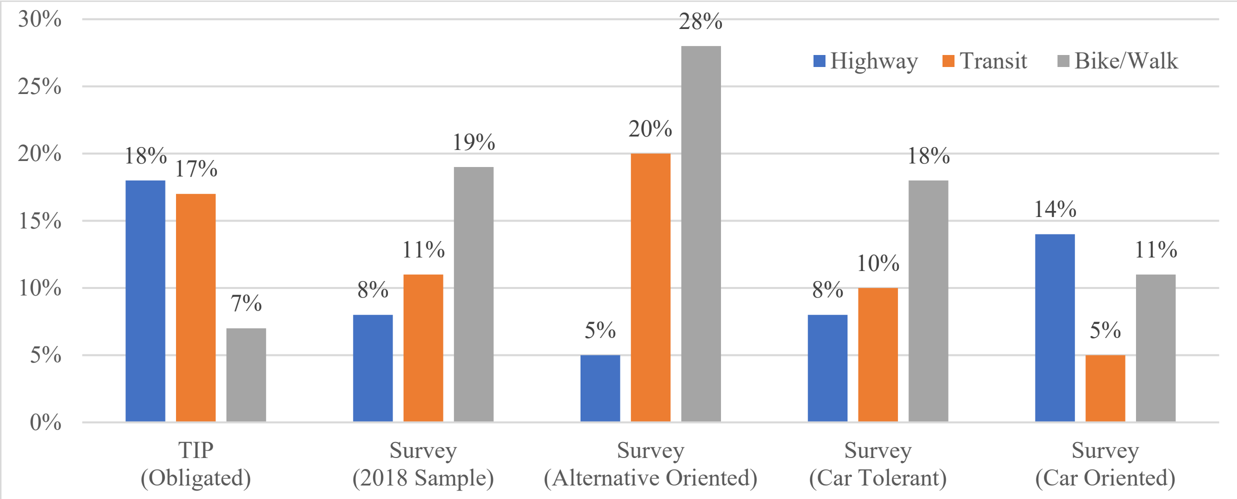

Figure 11 Share of Spending for Highways, Transit, and Bike/Walk Projects in the CCRPC TIP (Obligated) Compared to the Distribution of Points in the 2018 Survey Sample

Note: (1) Highway represents the "New Facility/Major Roadway Upgrades" category in the TIP (Obligated), and the "Highway Initiatives" category in the survey series. (2) Transit represents the "Transit" category in the TIP (Obligated), and the "Expanded Public Transportation Service" category in the survey series. (3) Bike/Walk represents the "Bike/Pedestrian" category in the TIP (Obligated), and the "Improved Bike/Walk Facilities" category in the survey series. (4) TIP (Obligated) represents spending across FY 2000 to FY 2018. (5) Number of Observations (N): Survey (Sample)= 413; Survey (Alternative Oriented)=104; Survey (Car Tolerant)=200; Survey (Car Oriented)=88.

Gas Taxes

Figure 12 and **Table 24** compile tabulations across the two survey questions regarding support for increasing gas taxes. For the pooled sample, a majority (58%) support increasing gas taxes in some capacity, while 42% do not. More respondents (26%) support increasing gas taxes to support non-highway projects (but not for exclusive use for highway projects) than support (8%) increasing gas taxes to exclusively support highway projects (but not for spending on non-highway projects). About a quarter of respondents (24%) support increasing gas taxes both for exclusive use for highway projects and for non-highway projects. Across the modal orientations, support for increasing gas taxes in some capacity is highest (72%) among the Alternative Oriented, and lowest among the Car Oriented (44%). A clear pattern emerges in support for increasing gas taxes for non-highway projects, with 69% among the Alternative Oriented cluster compared to 46% for the Car Tolerant and 30% among the Car Oriented. In terms of trends over the course of the survey series, in 2000, 34% of the sample did not support increasing gas taxes in any capacity, compared to 44% in 2006, 49% in 2012, and 37% in 2018. Support for increasing taxes was therefore lowest in 2012, perhaps in response to economic conditions surrounding the Great Recession. Support in 2018 for increasing gas taxes exclusively for highways projects was significantly higher (41%) than in the three prior survey years (32%, 31%, and 26%, respectively) (**Figure 7**).

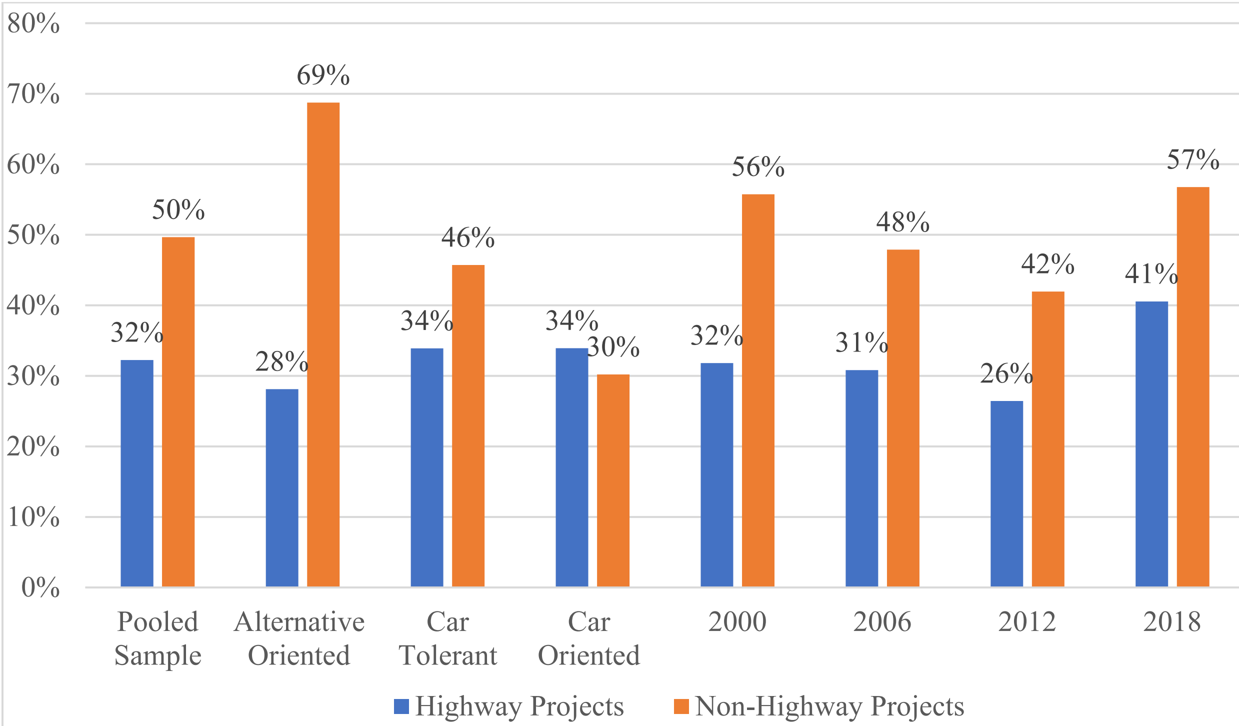

Figure 12 Support for Increasing Gas Taxes for Highway and Non-Highway Projects by Modal Orientation and Survey Year

Table 24 Support for Increasing Gas Taxes for Highway and Non-Highway Projects by Modal Orientation and Survey Year

	Do not support increasing gas taxes for non-highway projects	*Support increasing gas taxes for non-highway projects*
Pooled Sample (2000-2018)		
Do not support increasing gas taxes only for highway projects	42%	26%
Support increasing gas taxes only for highway projects	8%	24%
Alternative Oriented (N=416)		
Do not support increasing gas taxes only for highway projects	28%	44%
Support increasing gas taxes only for highway projects	4%	25%
Car Tolerant (N=721)		
Do not support increasing gas taxes only for highway projects	46%	20%
Support increasing gas taxes only for highway projects	8%	26%
Car Oriented (N=332)		
Do not support increasing gas taxes only for highway projects	56%	11%
Support increasing gas taxes only for highway projects	14%	20%
2000 (N=231)		
Do not support increasing gas taxes only for highway projects	34%	34%
Support increasing gas taxes only for highway projects	10%	21%
2006 (N=508)		
Do not support increasing gas taxes only for highway projects	44%	25%
Support increasing gas taxes only for highway projects	8%	23%
2012 (N=419)		
Do not support increasing gas taxes only for highway projects	49%	25%
Support increasing gas taxes only for highway projects	9%	17%
2018 (N=391)		
Do not support increasing gas taxes only for highway projects	37%	22%
Support increasing gas taxes only for highway projects	6%	35%

To build upon these binary tabulations, we employed binary logistic regression to model the likelihood of supporting a gas tax increase. The summary statistics for the samples used to model support for gas tax increases are presented in **Table 25**, and the results for the two models are presented in **Table 26**. The first model, which estimates the likelihood of supporting a gas tax increase for highways only, has much less explanatory power (Pseudo R2=0.051, PRE=0.0%), compared to the second model, which estimates the likelihood of supporting a gas tax increase for non-highway projects (Pseudo R2=0.151, PRE=39%). In both models, support for gas tax increases is significantly and positively associated with age, being male, and more education. Income was not a significant predictor in either model. Geographic location did not significantly predict support for increasing gas taxes for highway only projects, but lower density settings were significantly and negatively associated with support for increasing gas taxes for non-highway projects. Employment status was not a significant predictor for the first model, but the odds of supporting a gas tax increase for non-highway spending were significantly higher for those not in the labor force compared to the employed. In both models, the odds of supporting gas tax increases did not significantly differ between 2006 and 2012, but they were significantly higher in 2018 compared to 2006. In terms of modal orientations, the Car Tolerant cluster had significantly higher odds of supporting a gas tax increase in the first model but significantly lower odds in the second model. The odds did not differ between the Car Oriented and Alternative Oriented in the first model but were significantly lower for the Car Oriented in the second model.

Table 25 Summary Statistics for the Samples Regarding Support to Increase the Gas Tax

Variable	Obs	Mean	Min	Max	Variable	Obs	Mean	Min	Max
Support for Gas Tax Increase - Highway Only					***Support for Gas Tax Increase - Non-Highway***				
No	1,296	67%	0	1	No	1,319	50%	0	1
Yes	1,296	33%	0	1	Yes	1,319	50%	0	1
Age									
18-34 Years	1,296	22%	0	1	18-34 Years	1,319	22%	0	1
35-64 Years	1,296	62%	0	1	35-64 Years	1,319	61%	0	1
65+ Years	1,296	16%	0	1	65+ Years	1,319	16%	0	1
Education									
High School Diploma or Lower	1,043	10%	0	1	High School Diploma or Lower	1,319	10%	0	1
Some College or Associate Degree	1,296	23%	0	1	Some College or Associate Degree	1,319	22%	0	1
Bachelor's Degree or Higher	1,296	68%	0	1	Bachelor's Degree or Higher	1,319	68%	0	1
Employment Status									
Employed	1,296	80%	0	1	Employed	1,319	80%	0	1
Unemployed	1,296	2%	0	1	Unemployed	1,319	2%	0	1
Not in Labor Force	1,296	18%	0	1	Not in Labor Force	1,319	19%	0	1
Gender									
Female	1,296	51%	0	1	Female	1,319	50%	0	1
Male	1,296	49%	0	1	Male	1,319	50%	0	1
Geographic Location									
City	1,296	30%	0	1	City	1,319	30%	0	1
Suburb	1,296	45%	0	1	Suburb	1,319	45%	0	1
Small Town/Village	1,296	13%	0	1	Small Town/Village	1,319	13%	0	1
Rural	1,296	12%	0	1	Rural	1,319	12%	0	1
Income Quintile									
1 (Lowest)	1,296	11%	0	1	1 (Lowest)	1,319	11%	0	1
2	1,296	16%	0	1	2	1,319	16%	0	1
3	1,296	24%	0	1	3	1,319	24%	0	1
4	1,296	19%	0	1	4	1,319	19%	0	1
5 (Highest)	1,296	30%	0	1	5 (Highest)	1,319	30%	0	1
Modal Orientation									
Alternative Oriented	1,296	27%	0	1	Alternative Oriented	1,319	27%	0	1
Car Tolerant	1,296	51%	0	1	Car Tolerant	1,319	51%	0	1
Car Oriented	1,296	22%	0	1	Car Oriented	1,319	22%	0	1
Year									
2006	1,296	39%	0	1	2006	1,319	39%	0	1
2012	1,296	32%	0	1	2012	1,319	32%	0	1
2018	1,296	29%	0	1	2018	1,319	29%	0	1
Pooled Cross Sections (2006, 2012, 2018) Calibration Weights Applied					***Pooled Cross Sections (2006, 2012, 2018) Calibration Weights Applied***				

Table 26 Binary Logistic Regression Results (Likelihood of Supporting Gas Tax Increase)

Outcome: Support for Gas Tax Increase - Highway Only				Outcome: Support for Gas Tax Increase - Non-Highway			
Variable	**Odds Ratio**	**Std. Err.**	**P>|z|**	**Variable**	**Odds Ratio**	**Std. Err.**	**P>|z|**
Age							
18-34 Years	base			18-34 Years	base		
35-64 Years	1.6	0.3	0.01	35-64 Years	1.5	0.2	0.01
65+ Years	2.4	0.6	0.00	65+ Years	1.7	0.4	0.03
Gender							
Female	base			Female	base		
Male	1.9	0.2	0.00	Male	1.3	0.2	0.02
Education							
High School Diploma or Lower	base			High School Diploma or Lower	base		
Some College or Associate Degree	1.7	0.4	0.04	Some College or Associate Degree	2.4	0.6	0.00
Bachelor's Degree or Higher	1.6	0.4	0.05	Bachelor's Degree or Higher	4.8	1.2	0.00
Income Quintile							
1 (Lowest)	base			1 (Lowest)	base		
2	0.8	0.2	0.51	2	0.9	0.2	0.65
3	0.7	0.2	0.13	3	1.0	0.3	0.93
4	0.8	0.2	0.31	4	1.0	0.3	0.96
5 (Highest)	0.9	0.2	0.80	5 (Highest)	1.3	0.3	0.26
Geographic Location							
City	base			City	base		
Suburb	0.9	0.1	0.53	Suburb	0.6	0.1	0.00
Small Town/Village	0.8	0.2	0.23	Small Town/Village	0.5	0.1	0.00
Rural	0.8	0.2	0.31	Rural	0.7	0.1	0.07
Modal Orientation							
Alternative Oriented	base			Alternative Oriented	base		
Car Tolerant	1.3	0.2	0.08	Car Tolerant	0.4	0.1	0.00
Car Oriented	1.1	0.2	0.65	Car Oriented	0.1	0.0	0.00
Year							
2006	base			2006	base		
2012	0.8	0.1	0.24	2012	0.8	0.1	0.11
2018	1.5	0.2	0.01	2018	1.7	0.3	0.00
Employment Status							
Employed	base			Employed	base		
Unemployed	1.0	0.5	0.99	Unemployed	1.1	0.5	0.89
Not in Labor Force	1.1	0.2	0.60	Not in Labor Force	1.6	0.3	0.01
Constant	0.1	0.0	0.00	***Constant***	0.4	0.1	0.01
Total Observations: 1,296; Pseudo R2: 0.051; Proportional Reduction in Error: 0.000				Total Observations: 1,319; Pseudo R2: 0.151; Proportional Reduction in Error: 0.390			
Pooled Cross Sections (2006, 2012, 2018) Calibration Weights Applied				***Pooled Cross Sections (2006, 2012, 2018) Calibration Weights Applied***			

Discussion

Our analysis of spending by category indicates that the CCRPC is allocating more resources for highway projects (18%) than the general public (8%) or even the Car Oriented cluster (14%) would. However, it is also spending more on transit (17%) than the general public (11%) as well as the Car Tolerant (10%) and Car Oriented (5%) clusters (but not as much as the Alternative Oriented at 20%). Meanwhile, CCRPC is allocating less (7%) for biking and walking projects than the general public (19%) as well as all three modal orientations, including the Car Oriented (11%). Regional spending on alternatives (transit, biking, and walking combined) comprises about a quarter (24%) of all spending, compared to preferred distribution of 30% for the general public, 48% for the Alternative Oriented cluster, 28% for the Car Tolerant, and 16% for the Car Oriented. Overall, these results are consistent with prior findings of strong support for transportation spending on non-highway projects, such as transit (McCann, Kienitz et al. 2000). Regional decision-makers interested in decreasing automobile accommodations may find less resistance and more support for these efforts than previously understood, especially considering that the Alternative Oriented and Car Tolerant clusters together comprise over three-fourths of the general public.

Our analysis of support for increasing gas taxes suggests that, in general, modal orientations can help to explain these outcomes. As we might expect, the Alternative Oriented cluster is less supportive of increasing taxes only for highways (than the Car Tolerant, but not the Car Oriented) but more supportive of increasing taxes for non-highway spending, from which they could expect to directly benefit. We see an interesting similarity (or lack of significantly differing odds) in the odds of supporting gas taxes only for highway projects between the Alternative Oriented and Car Oriented. One possible explanation is that the Alternative Oriented do not support this because they perceive a lack of direct benefit, while the Car Oriented do not support this because they consume relatively high levels of fuel and therefore would stand to pay in more tax revenue. Even though the Car Tolerant at least occasionally use alternative modes, they still have significantly lower odds of supporting a gas tax increase for non-highway purposes. This may relate to the lower intensity with which the Car Tolerant rely on alternative modes compared to driving. Beyond modal orientations, our findings for age, education, and gender are consistent with significant and positive association of these variables found for support for increasing the gas tax in Dill and Weinstein (2007), but unlike that study, income was not significantly associated with the odds of supporting a gas tax increase of either type (highway only, or non-highway). The explanatory power of the first model is much lower than that for the binary logistic regression presented in Dill and Weinstein (2007), which had a Nagelkerke R2 of 0.12; however, our second model has a Pseudo R2 of 0.151 and improves upon chance in predicting the outcome by 39%. Finally, the univariate distributions of support for highway only (32% in the pooled sample) and non-highway (50%) purposes is largely consistent with prior findings of support for increasing gas taxes under 40-50%, but higher when connected to environmental benefits (Dill and Weinstein 2007, Agrawal and Nixon 2010, Agrawal and Nixon 2020).

Chapter 6: Conclusion

Table 27 presents a qualitative summary of this study's findings across the three categories of travel indicators, telecommunications, and planning priorities, by modal orientation. Together, these findings suggest the modal orientations represent a spectrum of automobile reliance (in terms of behavior) and support for automobile accommodation (in terms of planning).

One of the primary uses of traveler segmentation is concentrated marketing. A primary focus of limited outreach resources could be mode shift among the Car Tolerant, which comprises half the adult population in Chittenden County. This modal orientation group has a high willingness to change travel behavior with a change in travel conditions (Factor 1) and reports strong support for incentives for alternatives (Factor 7) (**Table 9**), but also perceives the car as the only option at a relatively high rate (Factor 2). The Car Tolerant could be encouraged to increase the intensity with which they use alternative modes and be introduced to supportive alternatives such as electric bicycles and carsharing. In contrast, the most effective strategies to market to the Car Oriented may be more fuel-efficient vehicles and greater use of telecommunications. For the Alternative Oriented, attention could be given to evaluating the barriers to even greater use of alternatives (such as use of employer-based transit subsidies). An overall shift in the distribution of the modal orientations away from automobile reliance could focus on investigating the underlying causes for Factor 1 (an openness to changing travel behavior) and Factor 2 (a perception of the car as the only option in most cases).

Beyond the modal orientations, our results indicate strong public support for a shift away from automobile accommodation and toward support for alternatives. The CC public would like fewer resources devoted to highways than is currently being allocated, and support for gas tax increases is higher for non-highway purposes than for use exclusive to highways. This may embolden CCRPC and other small urban MPOs (as well as state governments determining gas tax levels) to pursue greater conformance between the language used in their plans and the projects selected for funding and support (Mullin, Feiock et al. 2020). While transportation planning and travel behavior in the U.S. have historically reinforced an orientation toward the automobile, it is also possible to harness this cycle in support of alternative modes as well. Our findings suggest there is likely to be more public support for truly balanced transportation systems than has typically been understood or expected.

Table 27 Summary Matrix of Study Findings by Modal Orientation

	Alternative Oriented	Car Tolerant	Car Oriented	Basis
Travel Indicators				
Household Vehicles	0 Vehicles (Highest)	1-2 Vehicles (Highest)	3+ Vehicles (Highest)	Regression
Mode Use	Regular Transit, Bike, or Walk (Highest)	Regular Driver with Occasional Transit, Bike, or Walk (Highest)	Regular Driver Without Occasional Transit, Bike, or Walk (Highest)	Regression
Commuter Benefits	Parking Use (Lowest); Transit Use (Highest)	Parking Use (Middle); Transit Use (Middle)	Parking Use (Highest); Transit Use (Lowest)	Tabulation
Telecommunications				
Telework Availability	Even			Regression
Telework Interest	Higher (Even)		Lower	Tabulation
Telework Offer	Highest Use	Lowest Use	Middle Use	Tabulation
Trip Reductions Due to Internet	Medium	Highest	Lowest	Regression
Planning Priorities				
Spending by Category	Highway (Lowest); Transit (Highest); Bike/Walk (Highest)	Highway (Middle); Transit (Middle); Bike/Walk (Middle)	Highway (Highest); Transit (Lowest); Bike/Walk (Lowest)	Tabulation
Support for Gas Tax Increase - Highway Only	Lower (Even)	Highest	Lower (Even)	Regression
Support for Gas Tax Increase - Non-Highway	Highest	Middle	Lowest	Regression
Based on Regression Where Available (Otherwise Cross Tabulations for Pooled Samples)				

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