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PUGET SOUND REGIONAL COUNCIL

2019 PUGET SOUND REGIONAL TRAVEL STUDY

Final Report | March 30, 2020

PREPARED FOR:
PUGET SOUND REGIONAL COUNCIL

SUBMITTED BY:
RSG

IN COOPERATION WITH:
WESTGROUP RESEARCH

55 Railroad Row
White River Junction, VT 05001
802.295.4999
www.rsginc.com

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ACKNOWLEDGMENTS

The 2019 Puget Sound Regional Travel Study was supported by the efforts and advice of many partners. The Puget Sound Regional Council offers their thanks and appreciation to these agencies and their staff for their input on this study.

STUDY SPONSORS

- Puget Sound Regional Council.
- City of Seattle.

CONSULTANT TEAM

- RSG (Prime Consultant).
- WestGroup Research (Subconsultant).

GLOSSARY OF TERMS

TERM	DEFINITION
ABS	Address-based sampling (ABS) draws from a complete list of households within a given geographic area. This study's sampling frame was the full list of addresses in the specified census block groups as available from the United States Postal Service (USPS) Computerized Delivery Sequence File.
ACS	The American Community Survey (ACS) is an ongoing US Census Bureau survey that gathers demographic and other person- and household-level information. ACS estimates informed this study's sampling and weighting methods.
BG	A block group (BG) is a statistical division of a census tract and a contiguous geographic area that typically contains 600–3,000 people.
GPS	This study included a smartphone component that collected Global Positioning System (GPS) coordinates from participants' smartphone devices. GPS is a satellite system that collects both time and location (latitudinal and longitudinal) points.
Group	In the context of this study, a "group" refers to the mode through which households completed the travel diary portion of the study. Group 1 households completed Part 2 using rMove (a smartphone app), and Group 2 households completed Part 2 using rSurvey (an online survey platform). Groups were not assigned until each household completed Part 1 (the demographic and household information section).
HH	In this study, a household (HH) encompassed anyone who lives in the home, including roommates, relatives, friends, and household help.
HTS	A household travel survey (HTS) is a periodic survey that collects trip and other travel information from an entire household for a predefined period (at least one full day).
PSRC	The Puget Sound Regional Council (PSRC) "is a regional planning agency with specific responsibilities under federal and state law for transportation planning, economic development and growth management."[1]
RGC	The Puget Sound region includes 29 Regional Growth Centers (RGCs), which are "locations of the region's most significant business, governmental, and cultural facilities and are planning for growth."[2]
rMove™	rMove is a smartphone app designed to collect complete household travel diary information from invited participants. The app is compatible with most Android and iOS phones that are less than four years old. The study was designed to allow approximately 33% of participants to complete Part 2 using rMove.
rSurvey™	rSurvey is an online travel survey platform designed to collect complete household travel diary information from invited participants. All participants completed Part 1 using rSurvey, and approximately 66% of participants completed Part 2 of the study using rSurvey.
Travel date	In the context of this study, a "travel date" is the first (or only) day on which a household reported its trips.
UV	The City of Seattle has designated 41 areas as urban villages (UV). These are "areas in the city that are best able to absorb and capitalize on [future job and housing] growth."[3]

[1] Puget Sound Regional Council. "What We Do," https://www.psrc.org/about/what-we-do.
[2] Puget Sound Regional Council. "Centers," https://www.psrc.org/centers.
[3] City of Seattle. 2019. "Citywide Planning," http://www.seattle.gov/Documents/Departments/OPCD/OngoingInitiatives/SeattlesComprehensivePlan/CouncilAdopted2019_CitywidePlanning.pdf.

1.0 INTRODUCTION

1.1 STUDY OBJECTIVES

The 2019 Puget Sound Regional Travel Study followed the 2017 Puget Sound Regional Travel Study and was the second wave of a planned three-wave, six-year data collection effort. This effort will likely include one additional data collection wave in 2021. The 2019 study collected household- and person-level activity and travel pattern information from residents throughout the Puget Sound Regional Council (PSRC) four-county region from April–June of 2019.

The overarching goal of the multiyear program is to maintain an updated source of household travel behavior data that supports and allows for the following:

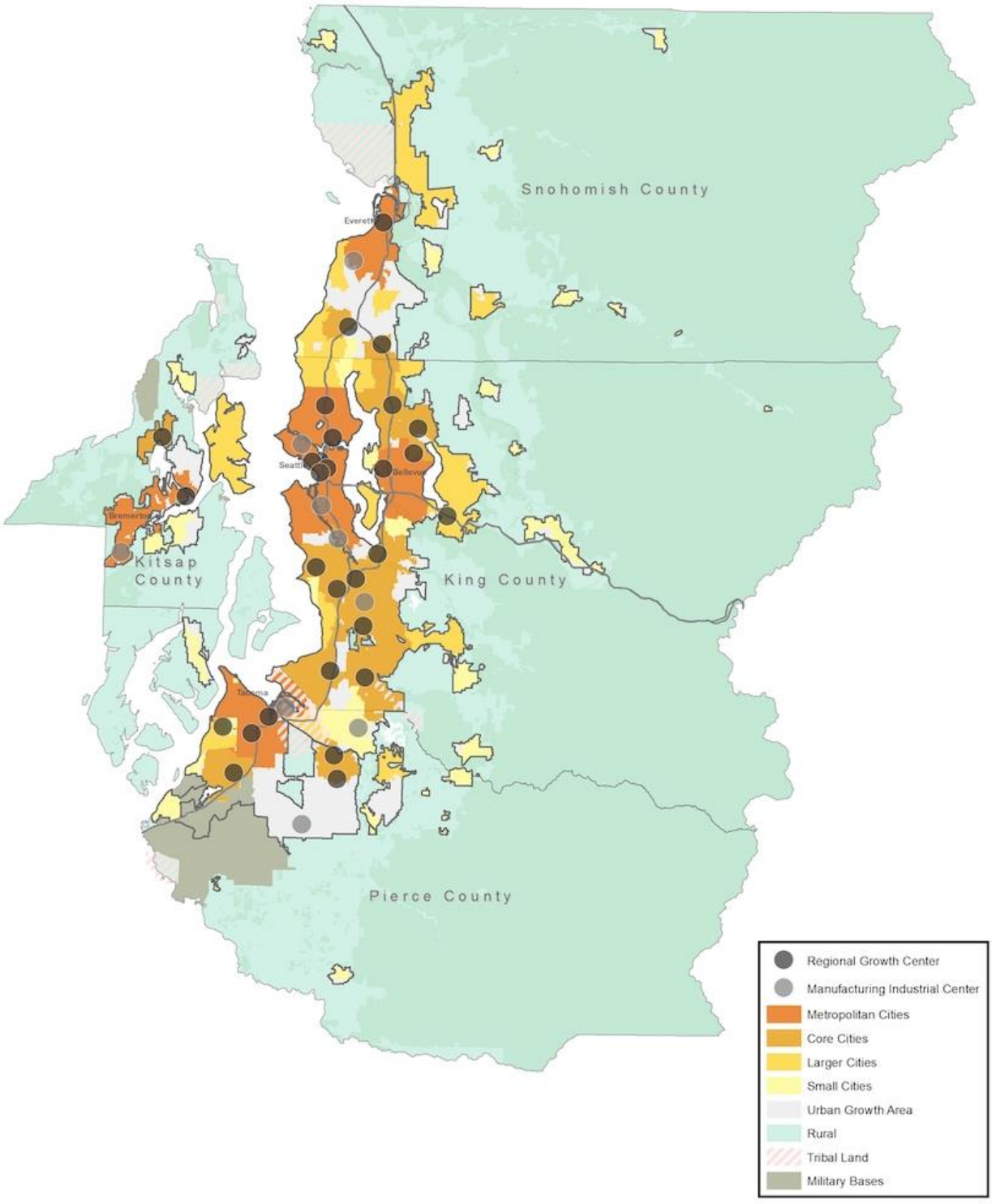
- Transportation and land-use modeling and planning needs.
- Trend analysis over time.
- Regular study design updates to integrate evolving data collection methods and emerging travel behaviors and transportation issues.

1.2 STUDY AREA

Consistent with recent surveys, the 2019 study encompassed the entire four-county PSRC region, which includes King, Kitsap, Pierce, and Snohomish counties. The region includes 82 cities and towns with a total population of over four million people. The study area comprises approximately 1,548,788 households.[4]

[4] Estimated residential household population from the American Community Survey 2013–2017 five-year estimates.

FIGURE 1: MAP OF STUDY AREA (PROVIDED BY PSRC)



Source: PSRC

1.3 STUDY TIMELINE

The scope of work for this project included both the design and administration of a one-day household travel diary (approximately 66% of households) and up to seven-day smartphone GPS diary (approximately 34% of households). Table 1 documents the project's schedule.

TABLE 1: STUDY TIMELINE

PHASE	TIMELINE
Scope Refinement	Sept. 2018–Jan. 2019
Survey Design	Dec. 2018–Apr. 2019
Survey Implementation	Apr. 2019–June 2019
Data Processing and Cleaning	June 2019–Dec. 2019
Documentation	June 2019–Jan. 2020
Data Analysis and Weighting	Nov. 2019–Jan. 2020
Project Closure	Mar. 2020

Source: RSG

2.0 SURVEY SAMPLING

2.1 SAMPLING GOALS

The 2019 study aimed to sample **2,750 complete households**, which equates to a **0.18% sample rate** (based on data from the 2013–2017 American Community Survey [ACS]). This sample goal included targets for the two sponsoring agencies:

- **PSRC**: 1,050 complete households in the four-county study region.
- **City of Seattle**: 1,700* complete households in Seattle's urban villages (UVs).

  (*This sample excludes any households in the City of Seattle surveyed in the core regional sample.)

Typical sample rates for similar studies range from approximately 0.5–1%. Across the 2017, 2019, and planned 2021 study, the combined sample rate will fall within this range. By comparison, the 2014 PSRC study (the last study prior to the three-wave design) had a sample rate of approximately 0.6%. The sections below further explain the process RSG used to determine the final sample rates for each census block group (BG).

2.2 SAMPLING METHODS

Sampling Frame

The primary sampling frame was the list of all households in the four-county study region of King, Kitsap, Pierce, and Snohomish counties.[5] RSG used address-based sampling (ABS) to select and invite households to participate in the study. ABS involves drawing a random sample of addresses from all the residential addresses in each sampling geography such that all households have an equal chance of selection for the sample. RSG purchased the final household mailing addresses from Marketing Systems Group, which maintains the Computer Delivery Sequence file from the USPS.

[5] The sampling frame was defined and stratified using ACS estimates of number of households in each census BG; based on these ACS estimates, 17 block groups with no households or few households (fewer than 50) were excluded from the sample analysis and final sample frame.

Stratification

The project contract required the high-level sample targets of 1,050 for PSRC and 1,700 for Seattle. The consultant team then determined target sample sizes by subregion (Table 2).

TABLE 2: TARGET SAMPLE SIZE, BY SUBREGION

SPONSOR	COUNTY	2013–2017 ACS HOUSEHOLDS	SAMPLE TARGET	TARGET SAMPLE RATE
PSRC	King (Excl. UVs)	723,680	400	0.06%
PSRC	Pierce	312,806	250	0.08%
PSRC	Snohomish	284,477	250	0.09%
PSRC	Kitsap	100,462	150	0.15%
City of Seattle	King (UVs)	127,363	1,700	1.33%
	PSRC Total	**1,421,425**	**1,050**	**0.07%**
	City of Seattle Total	**127,363**	**1,700**	**1.33%**
	Regional Total	**1,548,788**	**2,750**	**0.18%**

Source: RSG

Once the total sample targets were finalized for each subregion, the sample targets within each region were further stratified to achieve each agency's objectives. Strata were defined using BGs and ACS data.

City of Seattle Urban Village Stratification

The methodology used to set targets for each of the 41 UVs in the 2019 study was the same as the methodology used in the 2017 study; the one exception was that the number of households in each UV was based on the most current (2013–2017) ACS data and expected response rates were based on 2017 survey response rates (instead of a predicted rate). The general methodology was as follows:

1. Divide the UVs into three types: 1) urban centers; 2) urban hubs; and 3) residential UVs.
2. Set the minimum target for each type (following the targets from 2017): 40 completed surveys for urban centers, 30 for urban hubs, and 20 for residential UVs.
3. The sum of the minimum targets across the 41 UVs was 1,180 completed household surveys. The total target for the UVs was 1,760 (1,700 plus buffer); the remaining 580 completes were allocated across the UVs proportionally to the number of households in each UV.
4. Divide the target by the number of households living in each UV to calculate the target fraction of households in the final sample. Dividing that fraction by the expected response rate (the actual 2017 response rate) provided the percentage of households in the UV that RSG invited to reach the target.

5. Round the resulting percent up to one of nine values (15%, 20%, 25%, 30%, 35%, 50%, 60%, 90%, and 100%) to form aggregated sampling segments to address ordering process.

PSRC Stratification

Following the same approach as in the 2017 study, the 2019 study included a combination of simple geographic proportional sampling, “targeted oversampling” (sampling at higher rates in geographic areas of interest), and “compensatory sampling” (sampling at higher rates according to the expected response rates in different BGs).

Targeted Oversampling

Targeted oversampling in the 2019 study used nearly the same logic as the 2017 study. The targeted oversample segments included any BG that met any of the following criteria, based on data from the 2011–2015 ACS:

- BGs designated as part of an RGC.
- BGs where 35% or more of households (HHs) have income less than $25,000.
- BGs where 20% or more of HHs do not own a vehicle.
- BGs where 40% or more of workers do not commute by car.
- BGs where 40% or more of HHs are renters with head of household under age 35.

These variables are often spatially correlated across BGs—a high proportion of one or two variables means an increased likelihood that other variables are higher. However, to improve analysis, it was also important to identify BGs that were high in one variable but not others (e.g., BGs with high numbers of zero-vehicle households that are not located in urban/accessible areas). As in 2017, the sample objectives also included oversampling in RGCs.

Compensatory Oversampling

RSG used a model to identify compensatory oversample segments based on response rates from the 2017 study. This model segmented the BGs into high, medium, and low expected response rates. RSG applied a more conservative adjustment to the model results than in 2017, recognizing that overall survey response rates are decreasing.

Final Sample Segments

As in the 2017 study, the desired percentage of households for the oversample segments was roughly 2.5 times the desired percentage of households for the non-oversample segments. RSG varied the desired percentage of households up or down in each county to meet the sample targets (shown previously in Table 2).

Midstudy Adjustment and Final Sample Rates

After the first several weeks of data collection, RSG and PSRC observed that the response rates in some segments were much lower than in the 2017 study and beyond the buffer that was originally built into the sample plan. RSG and PSRC used 2019 response rates from the first half of the study to add invitations to sample segments that appeared behind target; the goal was to meet the original sample plan segment targets. The final invitation rates are included in Table 3.

TABLE 3: 2019 SAMPLING SEGMENTS AND INVITATION RATES

SUBREGION	SEGMENT	ACS HOUSEHOLDS (2013–2017)	DESIRED PERCENTAGE OF HOUSEHOLDS	TARGET SAMPLE SIZE	PREDICTED RESPONSE RATE	# OF INVITES (FINAL)
King	Regular–Low Response	110,440	0.035%	39	4.14%	942
King	Regular–Medium Response	164,582	0.035%	58	4.65%	1,247
King	Regular–High Response	289,020	0.035%	101	5.82%	1,736
King	Oversample–Low Response	57,914	0.090%	52	2.87%	1,809
King	Oversample–Medium Response	31,113	0.090%	28	1.94%	1,443
King	Oversample–High Response	70,611	0.091%	64	5.47%	1,169
King	**Total**	**723,680**	**0.047%**	**341**	**4.09%**	**8,346**
Pierce	Regular–Low Response	96,631	0.060%	58	2.53%	2,296
Pierce	Regular–Medium Response	109,888	0.060%	66	3.08%	2,144
Pierce	Regular–High Response	39,984	0.060%	24	1.04%	2,300
Pierce	Oversample–Low Response	55,798	0.160%	89	1.37%	6,516
Pierce	Oversample–Medium Response	10,505	0.162%	17	5.76%	295
Pierce	**Total**	**312,806**	**0.081%**	**254**	**1.87%**	**13,551**
Snohomish	Regular–Low Response	74,787	0.075%	56	2.84%	1,972
Snohomish	Regular–Medium Response	114,193	0.075%	86	4.40%	1,955
Snohomish	Regular–High Response	64,829	0.076%	49	3.59%	1,365
Snohomish	Oversample–Low Response	23,761	0.202%	48	3.60%	1,335
Snohomish	Oversample–Medium Response	6,907	0.203%	14	1.59%	881
Snohomish	**Total**	**284,477**	**0.089%**	**252**	**3.36%**	**7,508**
Kitsap	Regular–Low Response	32,315	0.121%	39	3.24%	1,202
Kitsap	Regular–Medium Response	36,906	0.119%	44	5.66%	777
Kitsap	Regular–High Response	9,871	0.122%	12	1.73%	692
Kitsap	Oversample–Low Response	10,671	0.281%	30	2.30%	1,302
Kitsap	Oversample–Medium Response	10,699	0.280%	30	4.53%	662
Kitsap	**Total**	**100,462**	0.154%	**155**	**3.34%**	**4,635**
PSRC	**PSRC Total**	**1,421,425**	0.070%	**1,002**	**2.94%**	**34,040**

SUBREGION	SEGMENT	ACS HOUSEHOLDS (2013–2017)	DESIRED PERCENTAGE OF HOUSEHOLDS	TARGET SAMPLE SIZE	PREDICTED RESPONSE RATE	# OF INVITES (FINAL)
UV	15% Invite Rate	49,504	0.879%	435	5.32%	8,178
UV	20% Invite Rate	28,502	1.091%	311	5.46%	5,699
UV	25% Invite Rate	17,926	1.238%	222	4.95%	4,483
UV	30% Invite Rate	10,472	1.891%	198	5.86%	3,378
UV	35% Invite Rate	9,853	1.776%	175	4.78%	3,660
UV	50% Invite Rate	4,710	3.206%	151	6.33%	2,384
UV	60% Invite Rate	1,491	3.152%	47	5.26%	894
UV	90% Invite Rate	2,305	3.080%	71	3.42%	2,074
UV	100% Invite Rate	2,600	5.885%	153	5.88%	2,600
City of Seattle	**Seattle Total**	**127,363**	**1.384%**	**1,763**	**5.29%**	**33,350**
Region	**Regional Total**	**1,548,788**	**0.179%**	**2,765**	**4.10%**	**67,390**

Source: RSG

2.3 SAMPLE MONITORING

Throughout the data collection period, RSG monitored response rates to ensure that the survey response was on target overall and by individual segment. This monitoring included a project tracking page that summarized live demographic distributions for households that completed at least Part 1 of the study. RSG and PSRC conducted a “midpoint review” after the first few weeks of data collection to determine whether adjustments were needed to help meet sampling objectives.

The consultant team monitored response at several levels:

- **Primary target**: Meet the total number of households for the study (2,750 HHs across the region).
- **Secondary target**: Ensure that the response is proportional in each sample segment.
- **Tertiary target**: Ensure that the response is proportional across demographics or geographic areas (e.g., by home county or region, UV, household size, income, and vehicle ownership).

During the data collection period, distinguishing between various levels of monitoring helped prioritize potential adjustments. For example, when the trends at the midpoint review indicated that survey response was lower than anticipated based on the 2017 study, the consultant team coordinated to send additional invitations to each sampling segment, proportionally distributed based on varying response. Table 3 reflects these adjustments.

3.0 SURVEY DESIGN

3.1 OVERVIEW

The 2019 study combined data collection methods, including smartphone, online, and telephone. As in the 2017 study, the goal of this design was to balance the strengths of innovative technologies with traditional experience and best practices derived from traditional market research. This approach balanced the need to adapt new survey methods over time with the need to collect comparable results and conduct trend analysis. The survey design included several stages to recruit and collect data about households, their members, and their travel behaviors during the assigned travel period.

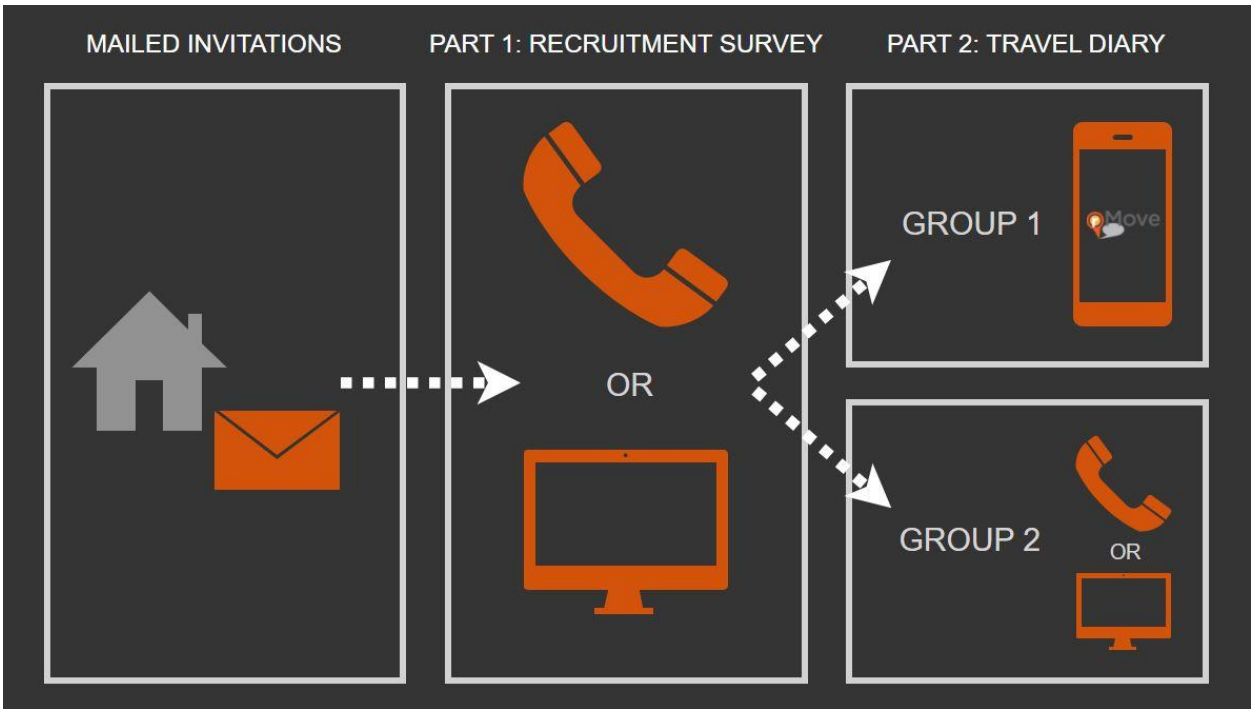
3.2 SURVEY STAGES AND PARTICIPATION METHODS

As explained in Section 2.0, this study used a traditional ABS approach, and RSG contacted invited households via mail (Section 4.0 provides additional detail about this process). The mailed study invitation materials instructed households to visit the study website or call a toll-free number to complete Part 1 (the demographic “recruit” survey). Households received instructions for Part 2 (the travel diary) after completing Part 1.

Study Components

All households completed Part 1 either via the online survey or through the call center. (When households contacted the call center, a representative utilized an identical online survey instrument, resulting in consistent data coding for telephone and online responses.) Part 1 collected general demographic information, established information to facilitate Part 2, and obtained any additional household-level information. Part 2 collected all trip and travel day information and any person-level information.

FIGURE 2: STUDY COMPONENTS AND GROUP ASSIGNMENTS



Source: RSG

Participation Group Assignments

Part 1 of the study included two questions about smartphone ownership. Participants over age 18 were asked to specify what type of smartphone they had (if any). RSG then used this information to determine group assignments. Group 2 participants were required to report their travel for one day online using rSurvey™, while Group 1 participants reported their travel for up to seven days using rMove™. The goal at the start of the study was to recruit approximately one-third of the total households for Group 1.

Unlike in the 2017 study, the 2019 study did not limit the number of households that could recruit into rMove at the study's launch. This change maximized rMove response and determined the upper limit of rMove recruitment for future waves using an opt-in design; in other words, eligible households could opt to use rMove for Part 2 but were not required to do so. Approximately 63% of eligible households opted into rMove for the 2019 study, which was higher than in the 2017 study (50%). To ensure the study met its rMove target for completed households, the consultant team added a quota (~200 households per week) to rMove opt-in beginning in week five of data collection.

Travel Date Assignments

All households were preassigned to a Tuesday, Wednesday, or Thursday travel date during the study period. Travel days were assigned randomly but were proportional across days and within segments. Households that opted into rMove participation were reassigned to a one-week travel period (always beginning on a Tuesday and ending on a Monday) following their completion of Part 1. This allowed time for each adult in the household to download rMove and prepare for their travel week.

Language Options

The survey (both online and rMove) was written entirely in English. Households that spoke Spanish, Russian, Chinese, Korean, Tagalog, Vietnamese, or Somali had the option to call the toll-free line to complete the survey over the phone in their preferred language. The online surveys also included a built-in Google translate bar that allowed participants to translate the survey into 103 different languages. Given that rMove was available in English only, the call center operators directed non-English-speaking households to opt out of completing the Part 2 survey in rMove. Approximately 90 households used the online Google translate tool to complete the survey (compared to 75 in 2017), and 10 completed the survey in a non-English language by phone.

3.3 SURVEY INCENTIVES

RSG offered $15 gift card incentives—as advertised on the study mailed materials—to each household completing Part 2 of the study using the online diary. Households that completed Part 2 of the study using rMove were offered $25 gift cards *per adult*.

Traditionally, transportation studies offer incentives to boost response rates and decrease the overall cost of mailed invitations (i.e., without incentives, the number of required households to invite increases. This increased mailing cost is greater than the cost of incentives). The increased response rates also help reduce nonresponse bias, producing a more trustworthy dataset.

Invited households could choose from physical or electronic gift cards from either Amazon.com or Starbucks. Households also had the option to opt out of receiving a gift card. These were the same options offered in the 2017 study, though the incentive amounts in the 2019 study were higher than the amounts in the 2017 study. In 2017, the rSurvey incentive was $10 per household, and the rMove incentive was $15 per adult.

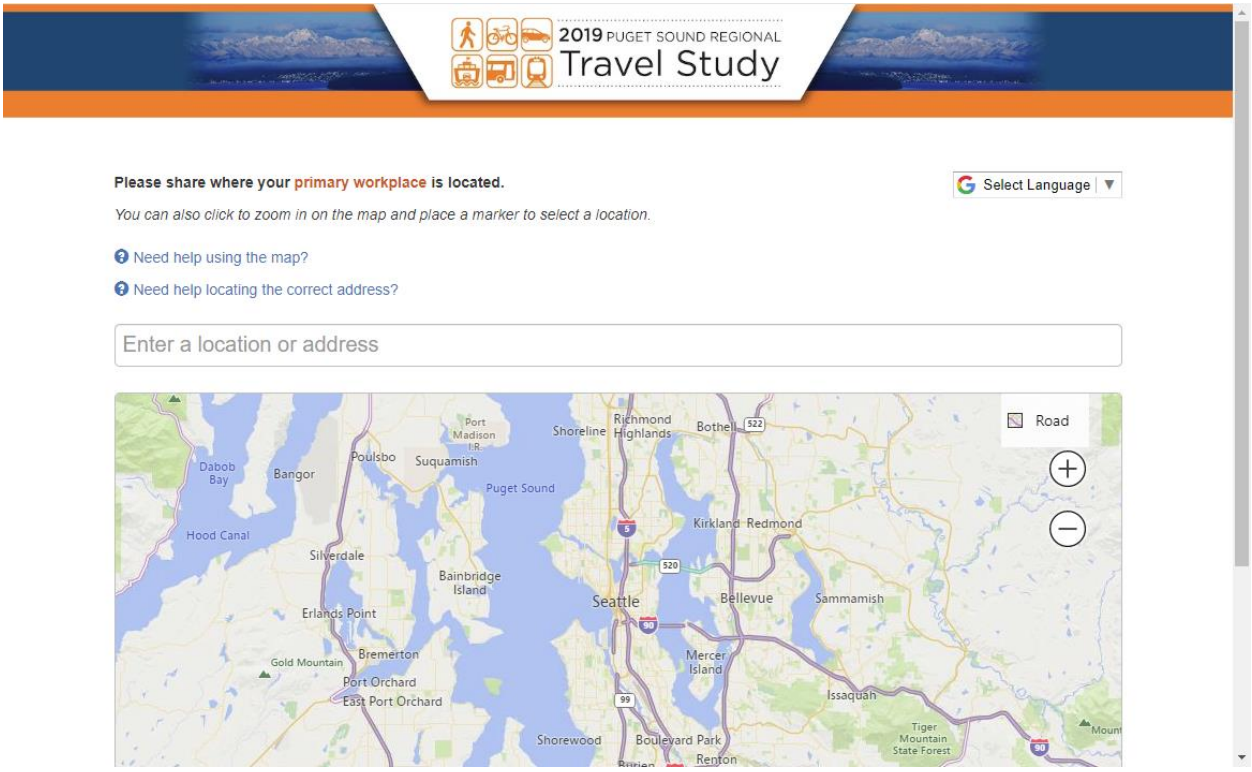
3.4 HOUSEHOLD, PERSON, AND VEHICLE DATA COLLECTED

Part 1 of the survey was the main collection source of household, person, and vehicle data. Households could complete this section any time after the study opened, and up to eight days after their assigned travel dates (when their household travel diaries closed). Part 1 was organized into the following question categories:

1. Vehicle ownership.
2. Household membership details (e.g., age, relationship, smartphone ownership).
3. Work and school information.
4. Home and previous home details.
5. Home location preferences and reasons for relocation (if applicable).
6. Household income.
7. Incentive and communication preferences.
8. Part 2 completion instructions.

The survey collected all address information for current and previous “habitual” locations (e.g., home address, work address, school address) using a built-in real-time geocoder (Figure 3). The full survey questionnaire is available in Appendix A.

FIGURE 3: PRIMARY WORKPLACE LOCATION GEOCODER (RECRUIT SURVEY SCREENSHOT)



Source: RSG

3.5 TRAVEL DIARY DATA COLLECTED

Trip Data

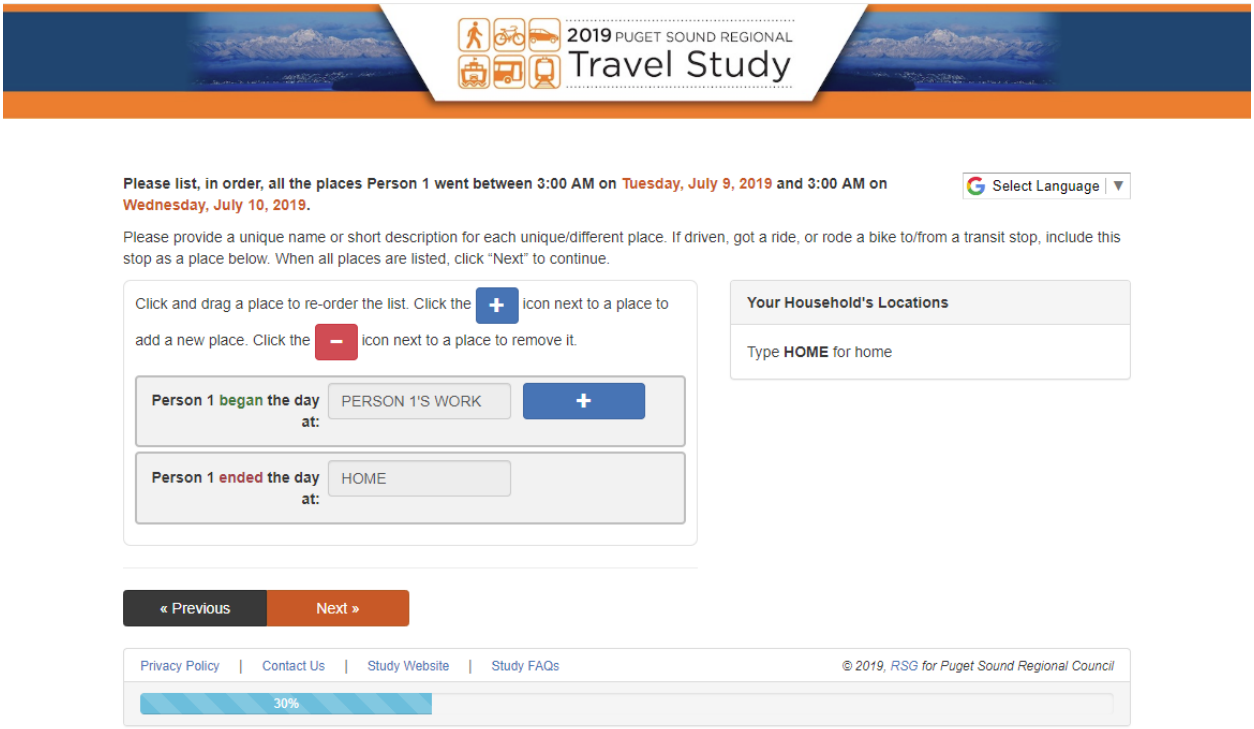
Although the rMove and rSurvey platforms varied slightly in user interface/design, each platform essentially captured the same information. Figure 4 and Figure 5 show example trip rosters in each platform. Both rMove and rSurvey gathered the following information from participants:

- Data obtained as explicit questions for both survey modes (rSurvey and rMove):
  - Travel party.
  - Trip purpose.
  - Travel mode(s).
  - Trip costs and other details associated with each mode (e.g., access/egress modes, parking details).
- Data passively obtained (without user input) by rMove and asked as explicit questions in rSurvey:
  - Trip start and end points.
  - Trip start and end times.
  - Trip roster.

Although the two platforms collected much of the same data, the collection method was not identical. Group 2 (rSurvey) participants reported all their trip information through recollection whereas rMove collected trip location and time details passively for Group 1 (rMove) participants. (Both groups recalled trip details that the app did not collect passively like travel party, trip purpose, and mode.) In practice, this often meant that trip start and end times were more specific among Group 1 trip diaries because rMove collected exact times, whereas Group 2 diaries only recorded times in five-minute increments.

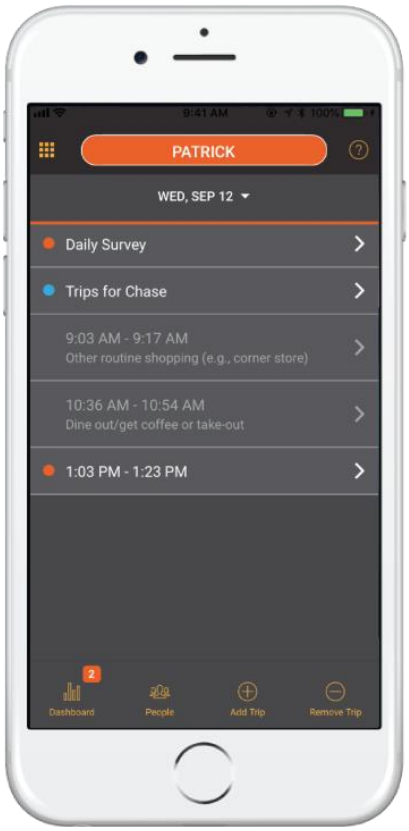
Moreover, when participants are asked to recall all the details of their trips, they frequently round departure and arrival times to the nearest 15 minutes (resulting in less-precise reports). Group 1 participants could correct passively collected trip data in rMove by splitting their trips into multiple segments, merging their trips, or adding entire trips. They could also report rMove errors (e.g., erroneous/spurious trips). Approximately 3.9% of rMove trips in the final dataset were edited by participants. Group 1 (rMove) participants were still asked to recall their trip purposes and travel parties, among other details.

FIGURE 4: RSURVEY TRIP ROSTER (SCREENSHOT)



Source: RSG

FIGURE 5: RMOVE TRIP ROSTER (SCREENSHOT)



Source: RSG

Travel Day Data

In addition to all trip data, the surveys collected day-level information at the end of each travel day (one day for rSurvey participants and up to seven days for rMove participants). In both cases, this information included the following:

- Why the participant made no trips that day (when that was the case).
- Types of deliveries that occurred that day.
- How much time the participant spent telecommuting or shopping online that day.

Reporting Travel for Children by Proxy

Although Part 1 collected information on all household members, Part 2 did not require the same level of participation for both children and adults. Adults participating through rSurvey were required to complete full travel diaries for all children between the ages of 5 and 18. During postprocessing, RSG derived individual trip records for children under the age of five based on the trips on which they traveled (reported in the travel party on trips made by other household members). rMove asked Group 1 adults to provide trip information for children under age 18 when no household adult was on the trip (e.g., bus to school), but were *not* required to answer any day-level information for their children. In both rMove and rSurvey, adults were still asked to report children of any age when they were present within their travel parties.

3.6 ADDITIONAL DATA COLLECTED

The survey questionnaire also included questions about general travel behavior and preferences. These questions included the following:

- Typical travel and frequency of using different travel modes (how often the participant typically walks, bikes, or uses transit, ridesharing, or carsharing systems).
- (If uses transit) availability and use of various transit fare payment methods (e.g., cash/tickets/Flex Pass).
- Employer transit subsidies and commuter benefits.
- Autonomous vehicle concerns and interests.
- Factors that would encourage increased bike/transit use.

Various questions were skipped based on age or reporting method. For example, if a participant was under age 16, then they were not asked about their use of carsharing systems. Also, if a participant's survey was reported by proxy (someone else was answering for them), then they were not asked opinion and preference questions.

3.7 SURVEY DESIGN UPDATES

While most of the survey design remained consistent with the 2017 study, there were several additions and changes. RSG and the study sponsors implemented these changes—listed in the sections below—to accommodate a combination of regional behavior/transportation shifts and new developments in survey research.

Structural Changes

In the 2017 study, rMove participants were asked to return to the online survey after completing their travel diary to respond to the preference questions listed previously. The 2019 study included these questions at the day level in rMove, removing the "third" step of the travel survey for rMove respondents. Due to formatting differences between the two survey instruments, RSG and the study sponsors agreed to include only a portion of the autonomous vehicle concern and interest questions in rMove to minimize the survey burden.[6]

In addition to content/layout changes, the 2019 study used Bing geocoders in the online survey, whereas the 2017 study used Google geocoders. This change was due to a change in the Google API pricing following the 2017 study. RSG conducted a thorough comparison of the two tools prior to implementation and found that there was no loss of data quality and the survey results were still comparable across years.

The following sections list all content changes in the 2019 study.

Content Changes: Added/Modified Questions

- **Relationship**: The answer options in this question were streamlined to reduce word count and improve clarity (e.g., updated "wife/husband/partner" to "spouse or partner").
- **Travel to school**: This question was added to determine whether students typically travel to school (preserving content previously collected in a dropped question).
- **Workplace**: The answer options were updated to clarify partial telework situations.
- **Work hours**: The answer options were updated to align with ACS data categories.
- **Reasons for leaving previous home location**: This added question was asked of all households that had moved within the past five years.
- **Travel modes**: The answer options were updated to reflect transportation trends in the region (e.g., added "scooter" option and revised carshare options).

The 2019 study also included several logistical updates to ensure that the survey was current. For example, RSG updated the list of vehicles from which participants could select their household vehicles' year/make/model.

[6] rMove asked participants to report their level of interest in owning an autonomous car, level of interest in participating in an autonomous car-share system for daily travel, level of concern about autonomous system and vehicle security, and level of concern about autonomous' cars ability to react to the environment (e.g., other cars, bicyclists, pedestrians, etc.).

Content Changes: Dropped Questions

The following questions were dropped from the 2019 study either to reduce survey burden or to keep the survey up to date:

- Smartphone age (previously used to determine rMove eligibility).
- Residence parking availability and cost.
- Travel day summary: Travel was typical or atypical of respondents' normal travel.
- Transit pass payment options among students.

4.0 SURVEY BRANDING, COMMUNICATION, AND ADMINISTRATION

4.1 STUDY BRANDING

RSG developed the 2019 study branding collaboratively with PSRC, reusing many design aspects from the 2017 study. The complete branding package included the study name, logo, color scheme, and font selections. The final 2019 study logo is shown in Figure 6.

FIGURE 6: 2019 STUDY LOGO

Source: RSG

4.2 STUDY INVITATION MATERIALS

Each invited household received three mailings:

- **Prenotice postcard**: RSG sent prenotice postcards to invite households in seven waves—each wave corresponded to a preassigned travel week. These postcards (arriving approximately 10 days before the household's assigned travel date) notified households that a formal study invitation would arrive shortly and that they would be offered an incentive after completing the study. The postcards also invited households to log on to the website or call the toll-free number to learn more about the study and to complete the first portion of the study.
- **Invitation packet**: Formal study invitation packets arrived at each household approximately three to four days before the assigned travel date. The cover letter explained the study purpose, described the steps necessary to complete the study, and included the study sponsors' logos and a signature from PSRC's executive director, Josh Brown. The invitation packet also included a Frequently Asked Questions (FAQ) sheet and foreign language insert with information about non-English participation (added in 2019).

- **Reminder postcard**: Reminder postcards arrived at each household approximately two or three days after the invitation packet to encourage every household to complete the study. Like the initial postcards, these cards included the study phone number, website address, and participant login information.

All mailings were written in English, but the postcards and letter also included separate phone numbers for non-English-speaking participants. The additional languages offered on the postcards and letter packet language insert were Spanish, Chinese, Korean, Russian, Tagalog, Vietnamese, and Somali. All languages were coordinated through the study call center. Example postcards are shown in Figure 7 (front) and Figure 8 (back), and examples of all printed materials can be found in Appendix B.

FIGURE 7: EXAMPLE SURVEY POSTCARD (FRONT)

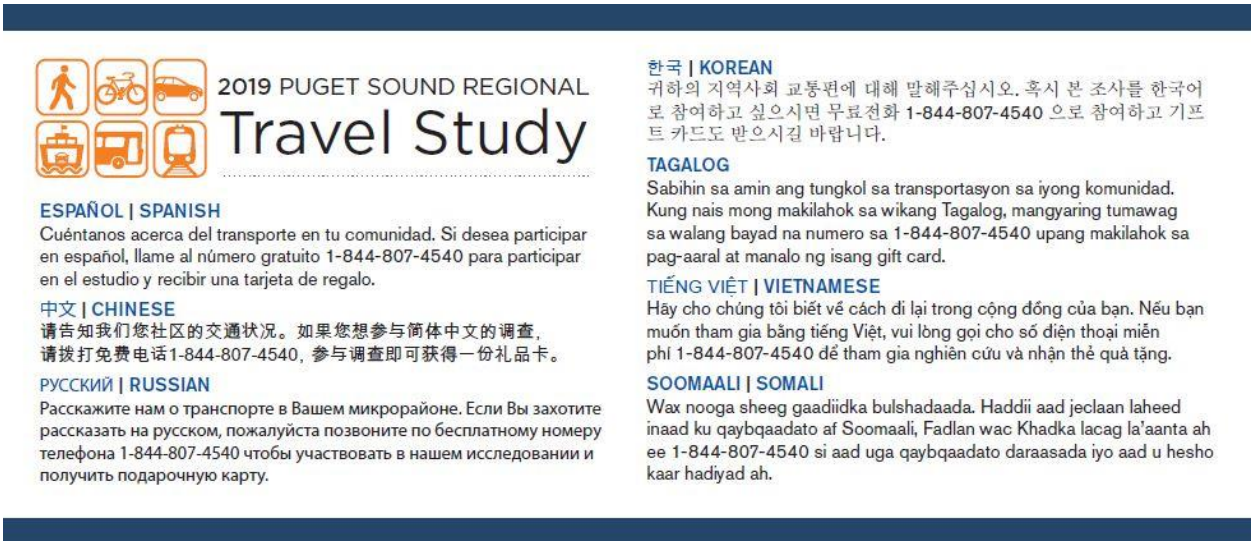
Source: RSG

FIGURE 8: EXAMPLE SURVEY POSTCARD (BACK)

Source: RSG

Changes to the printed materials in the 2019 study included adding a foreign language insert (Figure 9) and revising key study-specific details (e.g., updating the incentive and contact information).

FIGURE 9: FOREIGN LANGUAGE INSERT

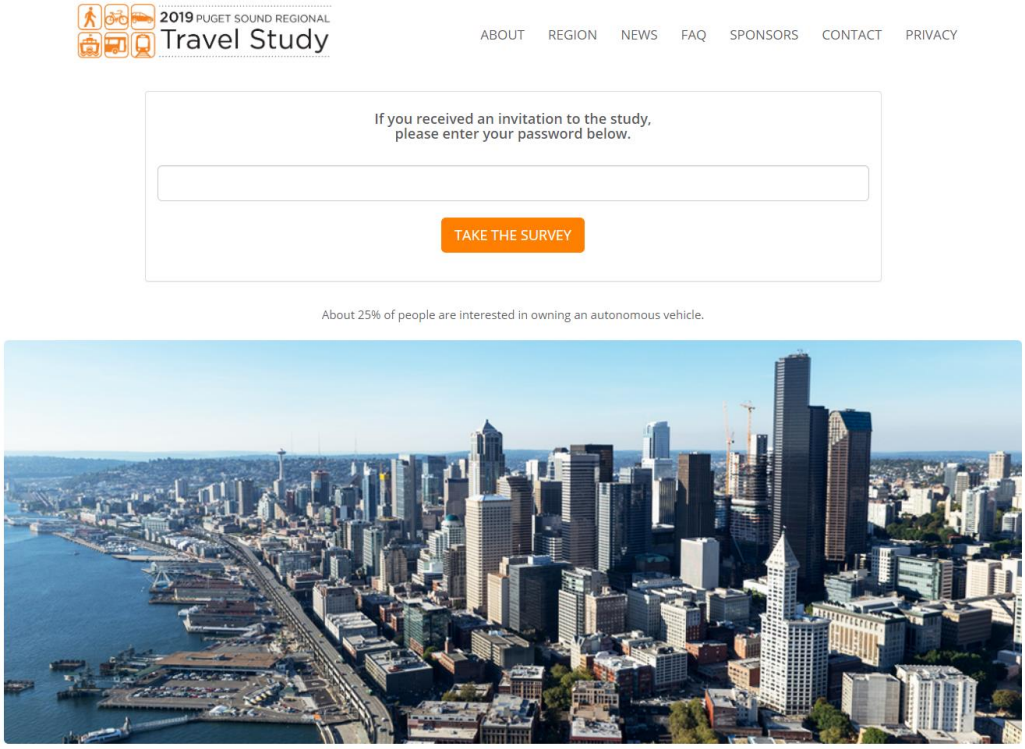


Source: RSG

4.3 STUDY WEBSITE

RSG developed a project website in 2014 to describe the 2014–2015 study and facilitate survey participation. RSG maintained this site in the interim and updated the design in 2017 and again in 2019 to reflect the new study and provide current information (e.g., updated FAQs, sponsors). The 2019 study website (like the 2014 and 2017 website) was designed to be simple, intuitive, and easy to navigate on desktop computers and mobile devices. The website home page is shown in Figure 10 below.

FIGURE 10: PROJECT WEBSITE HOME PAGE



Source: RSG

4.4 PUBLIC OUTREACH

Target Audiences

The primary goal of all outreach activities in a randomly sampled household travel survey (HTS) is to maximize participation from invited households. Effective public outreach achieves this goal through the following methods:

- Increasing invited households' understanding, awareness, and acceptance of the study.
- Communicating the importance of the study for local and regional planning needs.
- Legitimizing the study and creating trust that RSG and the study sponsors would use the collected data appropriately.

In the 2019 study, outreach activities were not limited to invited households, but the goal of all activities was to increase study response among those invited (i.e., outreach activities were not explicitly designed to recruit volunteers).

Outreach Actions

Beyond updating the study website, RSG and PSRC coordinated to develop a formal press release for PSRC and the City of Seattle to post on their respective websites and distribute to local media. PSRC also created and posted regular "Travel Survey Stories" to exemplify types of findings from HTS data.[7] RSG and PSRC also considered integrating targeted social media outreach – which was part of the 2017 survey outreach plan – but ultimately proceeded without targeted Facebook ads given that their impact in 2017 was inconclusive.

4.5 PARTICIPANT SUPPORT

Outbound Participant Support

RSG used several types of outbound participant support throughout the study. The primary sources included automated email reminders, reminder phone calls, and in-app reminders or notifications (rMove participants only).

Email Reminders and Phone Calls

During Part 1 of the survey, participants were required to provide a phone number or email address for study communications. All rMove participants were required to provide an email address, and any household that provided a phone number and email address was asked to specify a preferred method for study communications.

[7] Readers can view PSRC's travel stories here: https://www.psrc.org/household-travel-survey-program.

The study call center conducted all phone reminders to rSurvey households that only provided a phone number or specified phone as their preferred method of communication. Phone reminders occurred on the following schedule:

- **rSurvey users only**: One day before each household's travel date.
- **rSurvey users only**: One day after each household's travel date.
- **rSurvey users only**: Three to five days after each household's travel date (if the household had not yet completed the study).

RSG sent reminder emails on a more frequent schedule:

- **All participants**: Immediately after each household completed Part 1.
- **rMove users only**: Within 24 hours of completing Part 1. (This email included instructions to download the rMove app.)
- **rMove users only**: Four to zero days before travel period began (if all household participants had not downloaded the app).
- **All participants**: One day before travel date.
- **All participants**: One day after travel date/travel period end.
- **All participants**: Three to five days after travel date/travel period end (if the household had not yet completed the study).

In-App Reminders (rMove)

rMove participants also received in-app reminders to encourage them to complete all surveys during their travel periods. Participants got notifications as soon as a new survey was available—either several minutes after the end of a trip or the morning after a full travel day. rMove participants reporting for their children by proxy also received reminders to review and add to their children's trip rosters. Participants had the option to turn off reminders or GPS tracking, but RSG notifications and communications instructed them to leave these features enabled to ensure rMove could collect all travel data.

Inbound Participant Support

In addition to all outbound participant support, RSG provided three primary means through which participants could contact study administrators. Participants could call a toll-free number to reach the study call center or email the study inbox with questions. rMove participants also had the option to submit feedback directly through the app. The study website included the toll-free number, study email, and contact information for representatives from PSRC. Anyone with a question or comment could contact the consultant team or could contact PSRC directly for information, whether they were a participant or simply an interested member of the public.

Call Center

Participants who called the toll-free number were either connected to a trained representative who could answer any questions or asked to leave a voicemail. In total, the call center received 436 inbound calls, including 10 foreign language (5 Spanish, 3 Mandarin, and 2 Vietnamese) calls, and made 716 outbound calls (primarily reminder calls).

Email Inbox

RSG staff monitored and responded to the study email inbox and rMove feedback, typically within one business day. Table 4 below shows the breakout of inbound emails and rMove feedback messages, by primary topic.

TABLE 4: INBOUND EMAIL TOPICS

EMAIL TOPIC	COUNT
Gift card inquiry	168
General questions	76
Completion status	70
rMove troubleshooting	67
Comments and feedback	65
Out of town/Travel date reassignment request	51
Download questions/comments	48
rSurvey troubleshooting	43
Unsubscribe request	13
Forgot password	5
No reply needed (e.g., “thank you”)	2
Volunteer inquiry	1
Total	**609**

Source: RSG

5.0 DATASET PREPARATION

5.1 OVERVIEW

RSG conducted dataset preparation and quality control procedures at every stage of the study (before, during, and after data collection). These procedures were designed to validate survey logic, review participant experience, and confirm consistent data coding in the survey database. The following sections summarize the various dataset preparation and quality control steps. RSG provided a separate dataset user guide to PSRC with the initial dataset; this guide included data cleaning details for key elements.

5.2 DATASET PREPARATION

Database Setup and Real-Time Quality Controls

Prior to a survey launch, RSG and PSRC reviewed the survey instruments to ensure that the survey and app interfaces were clear and easy to use, questions were understandable, and variables wrote out to the database as expected. To reduce survey burden and improve final data quality, the survey also included real-time data checks and logic. Examples of these checks include the following:

- Validation logic to prevent skipped questions.
- Logic checks to hide irrelevant questions and answers (e.g., employment questions for children).
- Spatial and temporal checks within trip rosters to prevent overlapping trips.

These real-time data checks do not eliminate every inconsistency, but they do significantly reduce reporting errors and recoding requirements after data collection.

rMove also included tools to allow participants to validate or correct passively recorded trips during data collection. Participants could split trips, merge trips, or flag trips if they appeared to have other types of errors. These user-edits were flagged in the database for further analyst review after data collection.

Geographic Data Checks

RSG reviewed and processed rSurvey geographic data in several steps during and after data collection. (rMove GPS data are reviewed and processed separately as described in the next section.) During data collection, rSurvey used the Bing Maps API to geocode the coordinates for reported home, work, school, and trip addresses. The API was also used to estimate travel

times and distances. These estimates were recorded in the database and shown to participants in real time to help them verify that they had correctly entered their trip location information.

Following data collection, RSG reviewed trip distances and speed (by mode) and flagged for PSRC's review records with extreme values. RSG also coded home location points to BGs and broader regional definitions.

GPS Data Review and Quality Controls

Before combining the rMove and rSurvey datasets, RSG cleaned the rMove data in three primary stages:

1. **Automated data cleaning**: A machine-learning algorithm automatically classified trips (based on previous, manually reviewed datasets) to identify which trips should be automatically dropped, which should be kept as is (without additional review), and which trips were likely to need additional review by analysts in the next stage.
2. **Manual spatial review and correction**: Analysts reviewed trips to determine if one of three possible corrections should be applied to a trip:
   - **Drop/remove a trip from the dataset** (e.g., a participant walking around their yard or a trip that was generated due to an errant Wi-Fi signal).
   - **Split a trip where an additional stop was apparent** (e.g., a participant stops to drop off another household member at school on the way to work). In these cases, the answers from the initial trip were applied to all resulting trips after splitting. Trip purposes were later rederived based on known home/work/school locations where possible.
   - **Join or merge together two adjacent trips** (e.g., rMove loses signal on the highway and cuts out, but picks up a moment later further along the highway). In these cases, the analyst chose which trip survey answers should be applied to the resulting joined trip. The answers were typically the same for both surveys.
3. **Scripted processing and derivations**: The final stage included various scripted trip corrections and derivations on the initial cleaned dataset, including the following:
   - Imputing trips made by nonparticipating household members based on other participants' travel records (children in rMove households and children under five in online diary households). These trips typically represent only a portion of travel made by nonparticipants, which data users should consider when performing a trip-rate analysis or other analyses that require a holistic picture of a person's travel. Derivation of nonparticipant trips in the online diary is described in more detail in the next section.

- Removing locations with unreasonable derived speed or high-accuracy radius (based on a proprietary algorithm) and removing redundant locations that do not change the trajectories along a trip's path.
- Splitting "loop" trips (e.g., a walk around the block) into an outbound and return trip to and from the farthest point.[8] When a loop trip originated and ended at the participant's home location, the outbound trip destination purpose was coded to "other recreation" (these are often exercise or leisure trips).
- Unlinking transit trips, where possible.

Trip Derivation for Nonparticipating Household Members

HTS require data for all household members to assess complete household travel patterns. However, some exceptions are allowed in the data collection process where travel can be reported by proxy, particularly for children.

In the 2019 study, household adults were asked to report travel for the children in the household (under age 18 for rMove and ages 5–17 for rSurvey). Participants could also report children of all ages as travel party members on their own trips. RSG used these records to derive diary records for children under age 5 in households that used rSurvey to complete the study.

Integration of Data from Multiple Retrieval Modes

RSG combined, reviewed, and cleaned the data again after separately cleaning the rMove and rSurvey data. This process involved the following steps:

1. **Merge rMove and rSurvey variables**: In most cases, the daily and trip survey questions were identical or similar. However, in a few cases, the questions were formatted differently and resulted in slightly different variable types. Wherever feasible, RSG reconciled differences between variables (rather than keep them separate). In most cases, variables were recoded to retain as much detail as possible. These recoded variables included:
   - Trip mode and purpose.
   - Trip parking details.
   - Trip toll details.
   - Trip cost/payment details.
2. **Align the rMove and rSurvey travel days**: Traditionally, travel diaries collect data for a single 24-hour period—from 3:00 a.m. to 2:59 a.m. on the following day. This shift is used to account for trips that extend beyond (or take place after) midnight (e.g., shift workers or people returning from an evening out) but are still part of the "day" that ends

[8] Having distinct outbound/return trips, even on a valid loop trip, is often useful for building tours and other downstream modeling purposes.

at home. The rMove app collects travel diary data for multiple days and—for many reasons—currently defines midnight (calendar day) as the division between days.

To combine the rMove and rSurvey data into one, consistent dataset—and to retain the "traditional" travel day definition used in most travel models—the rMove "days" were redefined with 3:00 a.m. breakpoints. This resulted in the following outcomes:

- Trips that were recorded between midnight and 3:00 a.m. on a given day were assigned to the previous day trip totals/counts (e.g., trips between midnight and 3:00 a.m. on Saturday morning were flagged and counted as part of the "Friday" travel day).
- No trips were recorded between midnight and 3:00 a.m. after the last travel day (Monday), so this day does not cover a complete 24-hour period.

Some data elements in the combined dataset required derivation or slight adjustments due to differences between retrieval modes. For example, rSurvey obtained details that were not explicitly asked in rMove (e.g., transit routes and park-and-ride lots used, nicknames, and street addresses for trip destinations). Similarly, the rMove instrument obtained some details that were not asked in rSurvey (e.g., specific transit and parking costs).

Completion Criteria

The last step of dataset preparation involved reviewing all data records to confirm that they met survey, travel day, and household completion criteria. "Complete" households met the following conditions:

1. The household completed the online recruitment/demographic survey.
2. All household members provided complete travel diary information (i.e., answered all surveys and reported all trips) on at least one concurrent day during their travel period.
3. The household reported a home address within the study region.

All rSurvey households have a single complete travel day. rMove households must have at least one complete travel day (where all surveys are completed on the same day by all household members) but may have up to seven completed travel days. Partially complete rMove travel days are also included and flagged as such in the dataset.

6.0 EXPANSION AND WEIGHTING

Household travel surveys cover a fraction of the population, yet the resulting datasets help analyze and make inferences about the population at large. Weighting is the process of comparing selected demographics in the survey to external control data, like the census or the ACS, and adjusting the profile of the survey dataset to improve the representativeness of the population in the study area.

The full weighting memo, included in Appendix C, includes a detailed description of the weighting process for the 2019 study.

7.0 SURVEY RESULTS

7.1 SAMPLE PLAN EVALUATION

As mentioned in Section 2.0, the 2019 study aimed to sample **2,750 complete households** (1,050 households in the four-county study region + 1,700 additional households in Seattle's UVs). The four-county sample was stratified by county and expected response rate while the urban village sample was stratified only by response rate. Overall, both samples exceeded their targets for complete households. The estimated and final response rates and sample rates by sample segment are included in Table 5 and Table 6 below, respectively.

Note: The estimated sample rates in Table 6 are based on 2013-2017 ACS data (the most recent available at the time of sample plan development) while the actual sample rates are based on 2014-2018 ACS data. In some cases, this means that the final sample rate appears slightly below the estimated sample rate despite exceeding the completed household target.

TABLE 5: ESTIMATED AND ACTUAL RESPONSE RATE, BY SAMPLE SEGMENT

SUBREGION	SEGMENT	INVITED HOUSEHOLDS	COMPLETED HOUSEHOLDS	RESPONSE RATE (ESTIMATED)	RESPONSE RATE (ACTUAL)
King	Regular–Low Response	942	25	4.16%	2.65%
King	Regular–Medium Response	1,247	45	4.84%	3.61%
King	Regular–High Response	1,736	111	6.18%	6.39%
King	Oversample–Low Response	1,809	66	3.14%	3.65%
King	Oversample–Medium Response	1,443	69	2.31%	4.78%
King	Oversample–High Response	1,169	70	5.84%	5.99%
King	**Total**	**8,346**	**386**	**4.37%**	**4.62%**
Pierce	Regular–Low Response	2,296	68	2.81%	2.96%
Pierce	Regular–Medium Response	2,144	78	3.46%	3.64%
Pierce	Regular–High Response	2,300	102	1.32%	4.43%
Pierce	Oversample–Low Response	6,516	147	1.64%	2.26%
Pierce	Oversample–Medium Response	295	12	6.87%	4.07%
Pierce	**Total**	**13,551**	**407**	**2.19%**	**3.00%**

SUBREGION	SEGMENT	INVITED HOUSEHOLDS	COMPLETED HOUSEHOLDS	RESPONSE RATE (ESTIMATED)	RESPONSE RATE (ACTUAL)
Snohomish	Regular–Low Response	1,972	53	3.10%	2.69%
Snohomish	Regular–Medium Response	1,955	75	4.64%	3.84%
Snohomish	Regular–High Response	1,365	65	4.09%	4.76%
Snohomish	Oversample–Low Response	1,335	33	3.72%	2.47%
Snohomish	Oversample–Medium Response	881	37	1.90%	4.20%
Snohomish	**Total**	**7,508**	**263**	**3.65%**	**3.50%**
Kitsap	Regular–Low Response	1,202	22	3.44%	1.83%
Kitsap	Regular–Medium Response	777	38	6.59%	4.89%
Kitsap	Regular–High Response	692	29	2.11%	4.19%
Kitsap	Oversample–Low Response	1,302	34	2.59%	2.61%
Kitsap	Oversample–Medium Response	662	30	4.77%	4.53%
Kitsap	**Total**	**4,635**	**153**	**3.72%**	**3.30%**
PSRC	**PSRC Total**	**34,040**	**1,209**	**3.26%**	**3.55%**
UV	15% Invite Rate	8,178	522	5.38%	6.38%
UV	20% Invite Rate	5,699	310	5.52%	5.44%
UV	25% Invite Rate	4,483	230	5.26%	5.13%
UV	30% Invite Rate	3,378	211	5.91%	6.25%
UV	35% Invite Rate	3,660	173	4.82%	4.73%
UV	50% Invite Rate	2,384	142	6.34%	5.96%
UV	60% Invite Rate	894	47	6.18%	5.26%
UV	90% Invite Rate	2,074	66	3.83%	3.18%
UV	100% Invite Rate	2,600	134	6.00%	5.15%
City of Seattle	**Seattle Total**	**33,350**	**1,835**	**5.42%**	**5.50%**
Region	**Regional Total**	**67,390**	**3,044**	**4.33%**	**4.52%**

Source: RSG

TABLE 6: SAMPLE RATE, BY SAMPLE SEGMENT

SUBREGION	SEGMENT	ACS HOUSEHOLDS (2014-2018)	COMPLETED HOUSEHOLDS	SAMPLE RATE (ESTIMATED)	SAMPLE RATE (ACTUAL)
King	Regular–Low Response	111,663	25	0.04%	0.02%
King	Regular–Medium Response	166,225	45	0.04%	0.03%
King	Regular–High Response	292,329	111	0.04%	0.04%
King	Oversample–Low Response	58,279	66	0.09%	0.11%
King	Oversample–Medium Response	31,952	69	0.09%	0.22%
King	Oversample–High Response	71,680	70	0.09%	0.10%
King	**Total**	**732,128**	**386**	**0.05%**	**0.05%**
Pierce	Regular–Low Response	97,803	68	0.06%	0.07%
Pierce	Regular–Medium Response	111,524	78	0.06%	0.07%
Pierce	Regular–High Response	40,966	102	0.06%	0.25%
Pierce	Oversample–Low Response	56,515	147	0.16%	0.26%
Pierce	Oversample–Medium Response	10,883	12	0.16%	0.11%
Pierce	**Total**	**317,691**	**407**	**0.08%**	**0.13%**
Snohomish	Regular–Low Response	75,902	53	0.08%	0.07%
Snohomish	Regular–Medium Response	115,433	75	0.08%	0.06%
Snohomish	Regular–High Response	67,036	65	0.08%	0.10%
Snohomish	Oversample–Low Response	24,320	33	0.20%	0.14%
Snohomish	Oversample–Medium Response	7,046	37	0.20%	0.53%
Snohomish	**Total**	**289,737**	**263**	**0.09%**	**0.09%**
Kitsap	Regular–Low Response	32,255	22	0.12%	0.07%
Kitsap	Regular–Medium Response	37,387	38	0.12%	0.10%
Kitsap	Regular–High Response	10,137	29	0.12%	0.29%
Kitsap	Oversample–Low Response	11,085	34	0.28%	0.31%
Kitsap	Oversample–Medium Response	10,753	30	0.28%	0.28%
Kitsap	**Total**	**101,617**	**153**	**0.15%**	**0.15%**
PSRC	**PSRC Total**	**1,441,173**	**1,209**	**0.07%**	**0.08%**

SUBREGION	SEGMENT	ACS HOUSEHOLDS (2014-2018)	COMPLETED HOUSEHOLDS	SAMPLE RATE (ESTIMATED)	SAMPLE RATE (ACTUAL)
UV	15% Invite Rate	51,987	522	0.88%	1.00%
UV	20% Invite Rate	30,169	310	1.09%	1.03%
UV	25% Invite Rate	18,765	230	1.24%	1.23%
UV	30% Invite Rate	11,174	211	1.89%	1.89%
UV	35% Invite Rate	10,085	173	1.78%	1.72%
UV	50% Invite Rate	4,843	142	3.21%	2.93%
UV	60% Invite Rate	1,479	47	3.15%	3.18%
UV	90% Invite Rate	2,642	66	3.08%	2.50%
UV	100% Invite Rate	2,317	134	5.88%	5.78%
City of Seattle	**Seattle Total**	**133,461**	**1,835**	**1.38%**	**1.37%**
Region	**Regional Total**	**1,574,634**	**3,044**	**0.18%**	**0.19%**

Source: RSG

7.2 DEMOGRAPHICS BY PARTICIPATION GROUP

Table 7 through Table 14 below show the distribution of key demographics by diary participation group. Overall, rMove diary participants tend to be younger, are more often employed, and more often live in zero-vehicle households. This is notable given that these factors strongly impact travel behaviors. Household income, which also tends to influence travel behavior, is fairly consistent between the two groups.

TABLE 7: HOUSEHOLD SIZE, BY PARTICIPATION GROUP

HOUSEHOLD SIZE	RMOVE DIARY (UNWEIGHTED COUNT)	ONLINE DIARY (UNWEIGHTED COUNT)	RMOVE DIARY (WEIGHTED COUNT)	ONLINE DIARY (WEIGHTED COUNT)	RMOVE DIARY (UNWEIGHTED %)	ONLINE DIARY (UNWEIGHTED %)	RMOVE DIARY (WEIGHTED %)	ONLINE DIARY (WEIGHTED %)
1 person	462	840	146,724	300,313	44.1%	42.1%	27.6%	26.0%
2 people	397	784	164,767	452,846	37.9%	39.3%	31.0%	39.2%
3 people	101	197	84,160	189,264	9.6%	9.9%	15.8%	16.4%
4 people	62	132	84,776	145,779	5.9%	6.6%	15.9%	12.6%
5+ people	25	44	51,183	66,064	2.4%	2.2%	9.6%	5.7%
Total	**1,047**	**1,997**	**531,610**	**1,154,267**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 8: HOUSEHOLD INCOME, BY PARTICIPATION GROUP

HOUSEHOLD INCOME	RMOVE DIARY (UNWEIGHTED COUNT)	ONLINE DIARY (UNWEIGHTED COUNT)	RMOVE DIARY (WEIGHTED COUNT)	ONLINE DIARY (WEIGHTED COUNT)	RMOVE DIARY (UNWEIGHTED %)	ONLINE DIARY (UNWEIGHTED %)	RMOVE DIARY (WEIGHTED %)	ONLINE DIARY (WEIGHTED %)
Under $25,000	89	194	70,193	98,380	8.5%	9.7%	13.2%	8.5%
$25,000-$49,999	155	284	61,270	179,871	14.8%	14.2%	11.5%	15.6%
$50,000-$74,999	157	310	78,220	162,482	15.0%	15.5%	14.7%	14.1%
$75,000-$99,999	147	270	80,554	134,060	14.0%	13.5%	15.2%	11.6%
$100,000 or more	461	790	209,610	472,842	44.0%	39.6%	39.4%	41.0%
Prefer not to answer	38	149	31,764	106,632	3.6%	7.5%	6.0%	9.2%
Total	**1,047**	**1,997**	**531,610**	**1,154,267**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 9: HOUSEHOLD VEHICLES, BY PARTICIPATION GROUP

HOUSEHOLD VEHICLES	RMOVE DIARY (UNWEIGHTED COUNT)	ONLINE DIARY (UNWEIGHTED COUNT)	RMOVE DIARY (WEIGHTED COUNT)	ONLINE DIARY (WEIGHTED COUNT)	RMOVE DIARY (UNWEIGHTED %)	ONLINE DIARY (UNWEIGHTED %)	RMOVE DIARY (WEIGHTED %)	ONLINE DIARY (WEIGHTED %)
0 (no vehicles)	233	342	49,166	68,683	22.3%	17.1%	9.2%	6.0%
1	526	918	192,825	340,169	50.2%	46.0%	36.3%	29.5%
2	236	540	198,722	448,262	22.5%	27.0%	37.4%	38.8%
3+ vehicles	52	197	90,897	297,153	5.0%	9.9%	17.1%	25.7%
Total	**1,047**	**1,997**	**531,610**	**1,154,267**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 10: PERSON AGE, BY PARTICIPATION GROUP

PERSON AGE	RMOVE DIARY (UNWEIGHTED COUNT)	ONLINE DIARY (UNWEIGHTED COUNT)	RMOVE DIARY (WEIGHTED COUNT)	ONLINE DIARY (WEIGHTED COUNT)	RMOVE DIARY (UNWEIGHTED %)	ONLINE DIARY (UNWEIGHTED %)	RMOVE DIARY (WEIGHTED %)	ONLINE DIARY (WEIGHTED %)
Under 5 years old	123	182	130,676	119,212	6.3%	4.8%	9.7%	4.4%
5-11 years	120	186	187,250	194,194	6.2%	4.9%	14.0%	7.2%
12-15 years	48	88	78,343	122,805	2.5%	2.3%	5.8%	4.5%
16-17 years	17	37	20,367	66,831	0.9%	1.0%	1.5%	2.5%
18-24 years	112	144	75,196	156,184	5.8%	3.8%	5.6%	5.8%
25-34 years	618	839	252,701	393,896	31.7%	22.3%	18.8%	14.5%
35-44 years	405	626	269,008	384,116	20.8%	16.6%	20.0%	14.2%
45-54 years	228	450	166,472	480,570	11.7%	12.0%	12.4%	17.7%
55-64 years	151	503	99,119	261,039	7.8%	13.4%	7.4%	9.6%
65-74 years	99	478	57,301	371,548	5.1%	12.7%	4.3%	13.7%
75-84 years	26	183	5,654	137,886	1.3%	4.9%	0.4%	5.1%
85 or years older	0	48	0	21,307	0.0%	1.3%	0.0%	0.8%
Total	**1,947**	**3,764**	**1,342,088**	**2,709,587**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 11: PERSON GENDER, BY PARTICIPATION GROUP

PERSON GENDER	RMOVE DIARY (UNWEIGHTED COUNT)	ONLINE DIARY (UNWEIGHTED COUNT)	RMOVE DIARY (WEIGHTED COUNT)	ONLINE DIARY (WEIGHTED COUNT)	RMOVE DIARY (UNWEIGHTED %)	ONLINE DIARY (UNWEIGHTED %)	RMOVE DIARY (WEIGHTED %)	ONLINE DIARY (WEIGHTED %)
Male	934	1,794	637,413	1,366,618	48.0%	47.7%	47.5%	50.4%
Female	980	1,867	686,780	1,250,465	50.3%	49.6%	51.2%	46.1%
Another	8	19	3,115	16,817	0.4%	0.5%	0.2%	0.6%
Prefer not to answer	25	84	14,780	75,687	1.3%	2.2%	1.1%	2.8%
Total	**1,947**	**3,764**	**1,342,088**	**2,709,587**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 12: PERSON RACE OR ETHNICITY, BY PARTICIPATION GROUP (AGE 18+)

PERSON RACE OR ETHNICITY	RMOVE DIARY (UNWEIGHTED COUNT)	ONLINE DIARY (UNWEIGHTED COUNT)	RMOVE DIARY (WEIGHTED COUNT)	ONLINE DIARY (WEIGHTED COUNT)	RMOVE DIARY (UNWEIGHTED %)	ONLINE DIARY (UNWEIGHTED %)	RMOVE DIARY (WEIGHTED %)	ONLINE DIARY (WEIGHTED %)
African American alone	29	76	49,147	68,092	1.8%	2.3%	5.3%	3.1%
American Indian alone	1	14	283	17,394	0.1%	0.4%	0.0%	0.8%
Asian alone	219	308	99,281	182,783	13.4%	9.4%	10.7%	8.3%
Hispanic alone	49	76	55,932	81,937	3.0%	2.3%	6.0%	3.7%
Native Hawaiian or Pacific Islander alone	6	16	1,113	12,081	0.4%	0.5%	0.1%	0.5%
White alone	1,159	2,329	555,479	1,184,490	70.7%	71.2%	60.0%	53.7%
Other alone	25	47	43,306	79,398	1.5%	1.4%	4.7%	3.6%
Multiple ethnicities	102	165	43,645	93,615	6.2%	5.0%	4.7%	4.2%
Prefer not to answer	49	240	77,265	486,754	3.0%	7.3%	8.3%	22.1%
Total	**1,639**	**3,271**	**925,451**	**2,206,546**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 13: PERSON STUDENT STATUS, BY PARTICIPATION GROUP (AGE 18+)

PERSON STUDENT STATUS	RMOVE DIARY (UNWEIGHTED COUNT)	ONLINE DIARY (UNWEIGHTED COUNT)	RMOVE DIARY (WEIGHTED COUNT)	ONLINE DIARY (WEIGHTED COUNT)	RMOVE DIARY (UNWEIGHTED %)	ONLINE DIARY (UNWEIGHTED %)	RMOVE DIARY (WEIGHTED %)	ONLINE DIARY (WEIGHTED %)
Not a student	1,482	3,073	832,968	2,080,491	90.4%	93.9%	90.0%	94.3%
Part-time student	51	75	40,072	45,970	3.1%	2.3%	4.3%	2.1%
Full-time student	106	123	52,411	80,084	6.5%	3.8%	5.7%	3.6%
Total	**1,639**	**3,271**	**925,451**	**2,206,546**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 14: PERSON EMPLOYMENT STATUS, BY PARTICIPATION GROUP (AGE 18+)

PERSON EMPLOYMENT STATUS	RMOVE DIARY (UNWEIGHTED COUNT)	ONLINE DIARY (UNWEIGHTED COUNT)	RMOVE DIARY (WEIGHTED COUNT)	ONLINE DIARY (WEIGHTED COUNT)	RMOVE DIARY (UNWEIGHTED %)	ONLINE DIARY (UNWEIGHTED %)	RMOVE DIARY (WEIGHTED %)	ONLINE DIARY (WEIGHTED %)
Employed full time (35+ hours/week, paid)	1,069	1,742	542,342	1,145,612	65.2%	53.3%	58.6%	51.9%
Employed part time (fewer than 35 hours/week, paid)	143	285	112,570	161,458	8.7%	8.7%	12.2%	7.3%
Self-employed	108	238	34,791	131,509	6.6%	7.3%	3.8%	6.0%
Unpaid volunteer or intern	11	21	5,726	7,401	0.7%	0.6%	0.6%	0.3%
Homemaker	65	105	68,931	114,667	4.0%	3.2%	7.4%	5.2%
Retired	146	664	88,449	482,809	8.9%	20.3%	9.6%	21.9%
Not currently employed	97	216	72,642	163,090	5.9%	6.6%	7.8%	7.4%
Total	**1,639**	**3,271**	**925,451**	**2,206,546**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

7.3 TRIP RATES ON COMPLETE WEEKDAYS (MONDAY–THURSDAY)

Table 15 through Table 20 below show person trip rates on complete Mondays through Thursdays for key demographics and travel behaviors. (**Note**: The trip rates by day of week in Table 15 are based on the date of the trip departure timestamps.)

One of the most notable patterns in the tables below is the difference in trip rates between rMove and online diary participants. This is due to a combination of difference in demographics (e.g., rMove participants have a higher rate of employment) and a difference in data collection methods (rMove participants' trips are recorded in real time whereas online diary participants report their trips by recall and tend to under-report certain types of trips, like short-distance trips in the middle of the day). The trip weighting process (described in Appendix C) adjusts for these differences.

Section 7.4 and Section 7.5 show the weighted distribution of travel modes and trip purposes (respectively) by key variables including household income, age group, time of day, and trip distance.

TABLE 15: PERSON TRIP RATE, BY PARTICIPATION GROUP AND DAY OF WEEK

DAY OF WEEK	RMOVE DIARY (UNWEIGHTED TRIP RATE)	ONLINE DIARY (UNWEIGHTED TRIP RATE)	RMOVE DIARY (WEIGHTED TRIP RATE)	ONLINE DIARY (WEIGHTED TRIP RATE)
Monday	3.92	–	3.86	–
Tuesday	3.97	3.40	3.92	4.51
Wednesday	4.19	3.49	3.92	4.39
Thursday	4.29	3.47	4.49	4.86
Total	**4.09**	**3.45**	**4.05**	**4.56**

Source: RSG

TABLE 16: PERSON TRIP RATE, BY HOUSEHOLD INCOME

HOUSEHOLD INCOME	UNWEIGHTED DAYS	UNWEIGHTED TRIPS	WEIGHTED DAYS	WEIGHTED TRIPS	UNWEIGHTED TRIP RATE	WEIGHTED TRIP RATE
Under $25,000	712	2,440	337,556	1,297,800	3.43	3.85
$25,000-$49,999	1,321	4,848	516,647	2,077,806	3.67	4.02
$50,000-$74,999	1,466	6,071	537,166	2,506,834	4.14	4.67
$75,000-$99,999	1,370	5,073	467,107	1,851,359	3.70	3.96
$100,000 or more	5,170	20,706	1,902,488	9,028,373	4.01	4.75
Prefer not to answer	515	1,711	290,710	1,051,784	3.32	3.62
Total	**10,554**	**40,849**	**4,051,675**	**17,813,956**	**3.87**	**4.40**

Source: RSG

TABLE 17: PERSON TRIP RATE, BY AGE GROUP

AGE GROUP	UNWEIGHTED DAYS	UNWEIGHTED TRIPS	WEIGHTED DAYS	WEIGHTED TRIPS	UNWEIGHTED TRIP RATE	WEIGHTED TRIP RATE
Under 5 years old	615	1,847	249,888	763,070	3.00	3.05
5-11 years	599	1,800	381,444	1,062,793	3.01	2.79
12-15 years	253	800	201,148	564,592	3.16	2.81
16-17 years	92	288	87,198	325,259	3.13	3.73
18-24 years	538	2,081	231,380	922,941	3.87	3.99
25-34 years	3,029	12,184	646,597	2,958,132	4.02	4.58
35-44 years	2,029	8,635	653,124	3,582,286	4.26	5.49
45-54 years	1,227	5,236	647,042	3,410,738	4.27	5.27
55-64 years	1,013	3,803	360,158	1,636,111	3.75	4.54
65-74 years	831	3,050	428,849	1,869,306	3.67	4.36
75-84 years	280	1,020	143,540	638,639	3.64	4.45
85 or years older	48	105	21,307	80,091	2.19	3.76
Total	**10,554**	**40,849**	**4,051,675**	**17,813,956**	**3.87**	**4.40**

Source: RSG

TABLE 18: PERSON TRIP RATE, BY EMPLOYMENT STATUS (AGE 18+)

EMPLOYMENT STATUS	UNWEIGHTED DAYS	UNWEIGHTED TRIPS	WEIGHTED DAYS	WEIGHTED TRIPS	UNWEIGHTED TRIP RATE	WEIGHTED TRIP RATE
Employed full time (35+ hours/week, paid)	5,466	22,513	1,687,954	8,256,576	4.12	4.89
Employed part time (fewer than 35 hours/week, paid)	776	3,449	274,028	1,341,436	4.45	4.90
Self-employed	613	2,536	166,300	935,607	4.14	5.63
Unpaid volunteer or intern	61	257	13,127	64,717	4.21	4.93
Homemaker	337	1,407	183,598	1,080,962	4.18	5.89
Retired	1,184	4,165	571,258	2,413,560	3.52	4.23
Not currently employed	558	1,787	235,731	1,005,384	3.20	4.27
Total	**8,995**	**36,114**	**3,131,996**	**15,098,242**	**4.01**	**4.82**

Source: RSG

TABLE 19: PERSON TRIP RATE, BY TRAVEL MODE

TRAVEL MODE	UNWEIGHTED DAYS	UNWEIGHTED TRIPS	WEIGHTED DAYS	WEIGHTED TRIPS	UNWEIGHTED TRIP RATE	WEIGHTED TRIP RATE
(Nonresponse)	10,554	1	4,051,675	69	0.00	0.00
Walk	10,554	9,736	4,051,675	1,796,409	0.92	0.44
Bike	10,554	1,118	4,051,675	216,672	0.11	0.05
Car	10,554	24,282	4,051,675	14,584,081	2.30	3.60
Taxi	10,554	29	4,051,675	4,837	0.00	0.00
Transit	10,554	3,922	4,051,675	607,230	0.37	0.15
School bus	10,554	269	4,051,675	214,493	0.03	0.05
Other	10,554	302	4,051,675	131,132	0.03	0.03
Shuttle/Vanpool	10,554	366	4,051,675	135,820	0.04	0.03
TNC (Uber, Lyft, or other smartphone-app car service)	10,554	524	4,051,675	72,242	0.05	0.02
Carshare (e.g., ZipCar, Car2Go)	10,554	116	4,051,675	4,736	0.01	0.00
Bikeshare	10,554	31	4,051,675	820	0.00	0.00
Scooter or e-scooter (e.g., Lime, Bird, Razor)	10,554	11	4,051,675	4,925	0.00	0.00
Long distance (e.g., airplane)	10,554	142	4,051,675	40,492	0.01	0.01
Total	**10,554**	**40,849**	**4,051,675**	**17,813,956**	**3.87**	**4.40**

Source: RSG

TABLE 20: PERSON TRIP RATE, BY TRIP PURPOSE

TRIP PURPOSE	UNWEIGHTED DAYS	UNWEIGHTED TRIPS	WEIGHTED DAYS	WEIGHTED TRIPS	UNWEIGHTED TRIP RATE	WEIGHTED TRIP RATE
(Nonresponse)	10,554	21	4,051,675	4,662	0.00	0.00
Home	10,554	13,642	4,051,675	5,666,461	1.29	1.40
Work	10,554	5,525	4,051,675	2,080,954	0.52	0.51
Work-related	10,554	2,020	4,051,675	741,815	0.19	0.18
School	10,554	1,140	4,051,675	620,630	0.11	0.15
Escort	10,554	2,274	4,051,675	1,284,815	0.22	0.32
Shop	10,554	3,740	4,051,675	2,270,964	0.35	0.56
Meal	10,554	2,933	4,051,675	1,132,392	0.28	0.28
Social/Recreation	10,554	4,978	4,051,675	1,913,804	0.47	0.47
Errand/Other	10,554	4,384	4,051,675	2,026,075	0.42	0.50
Change mode	10,554	192	4,051,675	71,385	0.02	0.02
Total	**10,554**	**40,849**	**4,051,675**	**17,813,956**	**3.87**	**4.40**

Source: RSG

7.4 PERCENTAGE OF TRIPS BY TRAVEL MODE (WEIGHTED)

TABLE 21: TRAVEL MODE, BY HOUSEHOLD INCOME

TRAVEL MODE	UNDER $25,000	$25,000–$49,999	$50,000–$74,999	$75,000–$99,999	$100,000 OR MORE	PREFER NOT TO ANSWER
Walk	12.5%	7.8%	8.1%	9.6%	11.4%	6.1%
Bike	0.6%	0.3%	1.0%	1.0%	1.7%	0.6%
Car	74.9%	85.8%	84.8%	81.7%	80.2%	90.3%
Taxi	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Transit	8.9%	4.5%	4.5%	3.0%	2.4%	1.3%
School bus	1.5%	0.5%	0.3%	2.1%	1.4%	0.9%
Other	0.2%	0.2%	0.8%	0.7%	1.0%	0.5%
Shuttle/Vanpool	0.7%	0.2%	0.2%	0.7%	1.1%	0.4%
TNC (Uber, Lyft, or other smartphone-app car service)	0.7%	0.6%	0.2%	1.0%	0.3%	0.0%
Carshare (e.g., ZipCar, Car2Go)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Bikeshare	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Scooter or e-scooter (e.g., Lime, Bird, Razor)	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%
Long distance (e.g., airplane)	0.0%	0.1%	0.1%	0.1%	0.4%	0.0%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 22: TRAVEL MODE, BY AGE GROUP

TRAVEL MODE	UNDER 5 YEARS OLD	5–11 YEARS	12–15 YEARS	16–17 YEARS	18–24 YEARS	25–34 YEARS	35–44 YEARS	45–54 YEARS	55–64 YEARS	65–74 YEARS	75–84 YEARS	85 OR YEARS OLDER
Walk	9.0%	5.7%	9.8%	3.3%	15.6%	11.8%	9.4%	8.4%	15.7%	8.5%	9.8%	12.1%
Bike	0.8%	1.7%	0.8%	0.0%	0.7%	0.8%	2.0%	1.7%	1.4%	0.3%	0.2%	0.0%
Car	89.6%	76.2%	76.1%	89.8%	71.8%	77.2%	85.2%	84.5%	77.1%	85.8%	87.6%	80.8%
Taxi	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%
Transit	0.1%	0.7%	0.6%	1.2%	7.0%	7.1%	2.2%	2.5%	3.6%	4.7%	1.1%	0.5%
School bus	0.0%	12.4%	10.0%	3.8%	1.5%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Other	0.0%	0.0%	0.0%	0.6%	1.9%	0.7%	0.3%	1.7%	0.9%	0.2%	0.9%	0.0%
Shuttle/Vanpool	0.0%	3.3%	2.7%	0.0%	0.3%	0.8%	0.7%	0.6%	0.2%	0.0%	0.3%	6.7%
TNC (Uber, Lyft, or other smartphone-app car service)	0.0%	0.0%	0.0%	1.2%	0.8%	0.7%	0.2%	0.2%	1.0%	0.4%	0.0%	0.0%
Carshare (e.g., ZipCar, Car2Go)	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Bikeshare	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Scooter or e-scooter (e.g., Lime, Bird, Razor)	0.4%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
Long distance (e.g., airplane)	0.0%	0.0%	0.0%	0.0%	0.2%	0.7%	0.1%	0.4%	0.0%	0.2%	0.0%	0.0%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 23: TRAVEL MODE, BY TIME OF DAY

TRAVEL MODE	AM PEAK: 6:00 A.M.–9:00 A.M.	MIDDAY: 9:00 A.M.–3:00 P.M.	PM PEAK: 3:00 P.M.–6:00 P.M.	EVENING: 6:00 P.M.–8:00 P.M.	NIGHT: 8:00 P.M.–6:00 A.M.
Walk	4.5%	8.0%	14.2%	11.1%	9.3%
Bike	0.1%	1.3%	0.5%	0.6%	1.9%
Car	90.3%	81.6%	81.7%	80.3%	82.6%
Taxi	1.4%	0.0%	0.0%	0.0%	0.0%
Transit	1.0%	4.3%	1.8%	3.1%	3.8%
School bus	0.9%	1.8%	0.9%	2.9%	0.0%
Other	0.7%	0.7%	0.4%	0.2%	1.2%
Shuttle/Vanpool	0.9%	1.4%	0.2%	0.9%	0.4%
TNC (Uber, Lyft, or other smartphone-app car service)	0.1%	0.6%	0.2%	0.3%	0.4%
Carshare (e.g., ZipCar, Car2Go)	0.0%	0.0%	0.0%	0.0%	0.0%
Bikeshare	0.0%	0.0%	0.0%	0.0%	0.0%
Scooter or e-scooter (e.g., Lime, Bird, Razor)	0.1%	0.1%	0.0%	0.0%	0.0%
Long distance (e.g., airplane)	0.0%	0.1%	0.1%	0.6%	0.3%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

7.5 PERCENTAGE OF TRIPS BY TRIP PURPOSE (WEIGHTED)

TABLE 24: TRIP PURPOSE, BY HOUSEHOLD INCOME

TRIP PURPOSE	UNDER $25,000	$25,000–$49,999	$50,000–$74,999	$75,000–$99,999	$100,000 OR MORE	PREFER NOT TO ANSWER
Home	32.0%	28.6%	31.0%	35.0%	31.6%	35.8%
Work	5.6%	13.1%	10.7%	13.7%	12.3%	9.9%
Work-related	3.0%	4.4%	4.4%	5.5%	4.4%	0.4%
School	3.8%	2.7%	2.4%	3.6%	4.2%	1.4%
Escort	4.8%	5.0%	7.1%	5.1%	8.9%	4.2%
Shop	18.5%	16.9%	12.4%	13.2%	10.7%	15.0%
Meal	3.5%	6.3%	6.9%	5.2%	6.7%	7.9%
Social/Recreation	10.3%	11.3%	11.4%	8.3%	11.3%	8.2%
Errand/Other	18.3%	11.7%	12.5%	10.3%	9.5%	17.2%
Change mode	0.0%	0.1%	1.2%	0.1%	0.4%	0.0%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 25: TRIP PURPOSE, BY TIME OF DAY

TRIP PURPOSE	AM PEAK: 6:00 A.M.–9:00 A.M.	MIDDAY: 9:00 A.M.–3:00 P.M.	PM PEAK: 3:00 P.M.–6:00 P.M.	EVENING: 6:00 P.M.–8:00 P.M.	NIGHT: 8:00 P.M.–6:00 A.M.
Home	11.0%	13.1%	27.6%	46.2%	48.6%
Work	38.5%	24.9%	10.2%	2.8%	1.7%
Work-related	5.7%	5.5%	5.0%	3.5%	2.5%
School	0.1%	8.9%	1.6%	0.8%	0.4%
Escort	8.4%	9.2%	4.2%	10.1%	5.8%
Shop	0.3%	12.6%	19.0%	11.8%	9.7%
Meal	8.0%	3.5%	9.7%	4.1%	8.0%
Social/Recreation	16.2%	8.9%	7.6%	10.7%	14.6%
Errand/Other	5.9%	13.3%	14.5%	9.5%	8.4%
Change mode	5.8%	0.1%	0.6%	0.5%	0.3%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 26: TRIP PURPOSE, BY DISTANCE

TRIP PURPOSE	< 1 MILE	1–2 MILES	2–4 MILES	4–6 MILES	6–8 MILES	8–10 MILES	10–12 MILES	12–14 MILES	14–16 MILES	16–18 MILES	18–20 MILES	>= 20 MILES
Home	27.7%	32.3%	35.5%	34.9%	30.8%	27.4%	31.1%	29.3%	27.1%	37.2%	36.4%	33.0%
Work	8.8%	4.8%	6.8%	10.9%	13.9%	23.2%	13.1%	28.2%	24.5%	17.1%	35.4%	22.7%
Work-related	4.7%	3.6%	3.6%	4.8%	5.1%	3.6%	1.9%	3.6%	10.4%	4.2%	1.1%	4.3%
School	4.0%	5.2%	3.3%	3.5%	2.5%	0.9%	3.8%	0.2%	4.1%	1.8%	2.2%	2.0%
Escort	5.7%	9.7%	8.6%	8.2%	5.0%	4.3%	4.2%	2.2%	12.5%	7.2%	3.3%	5.8%
Shop	19.0%	13.3%	12.6%	9.9%	11.9%	7.3%	19.7%	14.0%	1.6%	1.8%	4.0%	8.0%
Meal	8.8%	6.1%	4.8%	5.2%	6.4%	15.4%	3.6%	2.1%	7.2%	7.8%	1.4%	3.0%
Social/ Recreation	11.4%	13.6%	10.5%	11.2%	8.8%	6.6%	12.0%	6.4%	3.4%	17.2%	11.7%	7.5%
Errand/Other	9.7%	11.3%	14.2%	11.1%	15.2%	10.9%	10.4%	14.1%	9.2%	5.3%	4.3%	10.8%
Change mode	0.2%	0.1%	0.1%	0.2%	0.4%	0.3%	0.1%	0.1%	0.1%	0.4%	0.2%	3.0%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

7.6 TRAVEL DAY ACTIVITIES (WEIGHTED)

In addition to providing details about each trip, participants were asked to provide travel replacement information for each day in their travel periods. This information included time spent working from home for pay, time spent shopping online, and home deliveries (including services). The weighted findings from these questions are included below in Table 27 through Table 29.

TABLE 27: SUMMARY OF TELEWORK TIME, BY DAY OF WEEK (AMONG EMPLOYED ADULTS)

TIME SPENT TELEWORKING ON TRAVEL DAY	MONDAY	TUESDAY	WEDNESDAY	THURSDAY
0–1 hour	4.5%	3.4%	3.4%	1.9%
1–2 hours	5.4%	3.6%	6.4%	3.3%
2–3 hours	1.0%	4.2%	1.7%	4.3%
3–4 hours	0.8%	1.2%	0.5%	0.6%
4–5 hours	0.8%	1.7%	0.7%	1.0%
5–6 hours	0.6%	0.6%	2.0%	2.3%
6–7 hours	0.1%	0.4%	1.1%	0.6%
7–8 hours	0.4%	1.1%	0.6%	0.9%
8+ hours	13.6%	12.2%	11.1%	8.3%
Did not telework	72.8%	71.5%	72.6%	76.8%
Total	**100.0%**	**100.0%**	**100.0%**	**100.0%**

Source: RSG

TABLE 28: SUMMARY OF TIME SPENT SHOPPING ONLINE

TIME SPENT TELEWORKING ON TRAVEL DAY	PERCENT (%)
0–1 hour	17.4%
1–2 hours	6.3%
2–3 hours	0.5%
3–4 hours	0.1%
4–5 hours	0.1%
5–6 hours	0.0%
6–7 hours	0.0%
7–8 hours	0.0%
8+ hours	0.0%
Did not shop online	75.4%
Total	**100.0%**

Source: RSG

TABLE 29: SUMMARY OF REPORTED DELIVERIES ON TRAVEL DAY

DELIVERIES ON TRAVEL DAY	PERCENT (%)
Packages	24.4%
Services	2.2%
Groceries	1.4%
Food / Meal Prep	0.5%
Multiple	2.8%
None	68.7%
Total	**100.0%**

Source: RSG

APPENDIX A. QUESTIONNAIRES

(See separate HTML files.)

APPENDIX B. INVITATION MATERIALS

(See separate PDF files.)

APPENDIX C. WEIGHTING MEMO

TO:	PSRC
FROM:	RSG
DATE:	January 24, 2020
SUBJECT:	Puget Sound Regional Travel Study: Weighting Methodology (2017 & 2019)

INTRODUCTION AND SCOPE

This memo describes the analysis, recommendations, and methodology used to expand[9] the data collected in the 2017 and 2019 Puget Sound Regional Travel Study to the 2018 American Community Survey Public Use Microdata Sample (ACS PUMS) data. The weighting methodology applied adjusts for survey nonresponse, survey participation mode, and geographic bias due to oversampling and other factors. In addition, RSG adjusted trip rates between the two participation methods (online diary and smartphone-app diary) offered for the survey in both years.

The applied weighting process included four primary steps:

1. **Initial Expansion**: Calculating an "initial weight" based on the probability of selection in the sample design. This essentially "reverses" the sample plan, providing higher initial weights to areas where less sampling occurred.
2. **Reweighting to account for nonresponse bias**: Performing an iterative proportional fit (IPF) routine to several key household and person dimensions to ensure the weighted data accurately represent the entire survey region (and reduce sampling biases).
    a. To do this step, a few missing data elements (income, gender, ethnicity, and race) need to be imputed for those who did not provide that information.
3. **Creating day-level weights to account for multiday survey data**: Adjusting the day-level and trip-level data to account for the fact that smartphone respondents provided multiday travel diaries, while online and call center respondents provided a single-day travel diary (this is the "multiday adjustment"). These relatively simple adjustments

[9] For the purposes of this memo, the terms expansion, expansion factors, and weights are used interchangeably and are synonymous. They all represent the concept of an expansion weight.

ensure that travel analyses accurately reflect the entire survey region and do not overrepresent smartphone respondents with multiple travel days.

4. **Adjusting for nonresponse bias in day-pattern and trip rates**: Adjusting the trip-level weights by data collection method (smartphone, online, call center) to account for reporting biases that RSG has detected in this survey and prior travel surveys. These adjustments help make the day-level and trip-level data more consistent and increase the accuracy of trip rates across survey participation methods.

The following sections describe this process and the results in detail. The overall goal is to make the survey sample representative of the entire survey area across several key dimensions related to travel behavior. Additionally, two sets of weights were calculated—one using data collected in 2019 only and one using a combination of the 2017 and 2019 datasets.

INITIAL EXPANSION FACTORS

The purpose of the initial expansion is to expand each complete survey record to the population that was eligible to participate in the survey. The initial expansion weights are based on the relative probabilities of each respondent has of being in the sample, as a function of the sampling plan and the number of invitations sent to specific sampling segments.

SELECTION OF RESPONDENTS FOR WEIGHTING

After the data processing is complete and any invalid person-days and household-days have been flagged as incomplete, any household which has at least one complete and valid weekday travel day will be included in the weighting. For this purpose, a complete weekday is any complete Monday, Tuesday, Wednesday, or Thursday. The selection of “weekdays” essentially assumes that trip rates and behavior on those days are similar enough to consider them interchangeable, with an average weekday being the average of travel across those days. Only those weekdays will be given person-day weights for analysis.

RSG did not weight travel data for Friday, Saturday, Sunday, or Monday because: 1) data were only collected from smartphone-participating households on those days; 2) the travel behavior for those days is not assumed to be interchangeable with the behavior for Monday–Thursday, and; 3) the data were used primarily to analyze and model typical weekday travel.

CALCULATION OF INITIAL EXPANSION WEIGHTS

To begin expanding the complete households, separate initial weights are calculated for each sampling segment. The study region was the same for the 2017 and 2019 surveys, so to calculate the initial expansion factors for the combined weighting, the population in each sampling strata was apportioned based on the relative sample sizes for each survey year. To

calculate the initial expansion factors for each stratum, the ratio of population household counts to sampled households is calculated.

The initial expansion weights are used as the starting weights for further reweighting to correct for nonresponse biases in the data, which is described in the following section.

Table 30 summarizes the initial expansion factors by sample segment. This includes initial expansion factors for the combined (2017 + 2019 study years) and the 2019-only datasets

TABLE 30: INITIAL EXPANSION FACTORS

SURVEY YEAR	SAMPLE SEGMENT	ACS HOUSEHOLD (2017 + 2019)	ACS HOUSEHOLD (2019 ONLY)	SAMPLED HOUSEHOLDS	INITIAL EXPANSION FACTOR (2017 + 2019)	INITIAL EXPANSION FACTOR (2019 ONLY)
2017	PSRC–Regular-Low	133,888	–	136	984.47	0.00
	PSRC–Regular-Medium	229,973	–	203	1,132.87	0.00
	PSRC–Regular-High	229,130	–	222	1,032.12	0.00
	PSRC–Oversample-Low	87,245	–	157	555.70	0.00
	PSRC–Oversample-Medium	25,038	–	66	379.36	0.00
	PSRC–Oversample-High	28,036	–	65	431.33	0.00
	Redmond–Regular-Medium	1,935	–	60	32.24	0.00
	Redmond–Regular-High	7,003	–	141	49.67	0.00
	Redmond–Oversample-Low	1,151	–	75	15.34	0.00
	Redmond–Oversample-Medium	869	–	36	24.14	0.00
	Redmond–Oversample-High	913	–	39	23.40	0.00
	Redmond–Downtown-Medium	407	–	71	5.73	0.00
	Redmond–Downtown-High	1,325	–	149	8.89	0.00
	UV 10%	18,850	–	218	86.47	0.00
	UV 15%	18,922	–	398	47.54	0.00
	UV 20%	7,416	–	177	41.90	0.00
	UV 25%	5,331	–	115	46.36	0.00
	UV 30%	5,656	–	194	29.16	0.00
	UV 35%	6,975	–	243	28.59	0.00
	UV 50%	1,893	–	120	15.77	0.00
	UV 60%	1,717	–	130	13.21	0.00
	UV 75%	1,019	–	74	13.78	0.00

SURVEY YEAR	SAMPLE SEGMENT	ACS HOUSEHOLD (2017 + 2019)	ACS HOUSEHOLD (2019 ONLY)	SAMPLED HOUSEHOLDS	INITIAL EXPANSION FACTOR (2017 + 2019)	INITIAL EXPANSION FACTOR (2019 ONLY)
	UV 100%	1,388	–	187	7.42	0.00
	UV 15%	25,044	51,987	522	47.98	99.59
	UV 20%	14,533	30,169	310	46.88	97.32
	UV 25%	9,040	18,765	230	39.30	81.59
	UV 30%	5,383	11,174	211	25.39	52.71
	UV 35%	4,858	10,085	173	28.08	58.29
	UV 50%	2,333	4,843	142	16.31	33.87
	UV 60%	712	1,479	47	15.16	31.47
	UV 100%	1,116	2,317	134	8.33	17.29
	UV 90%	1,273	2,642	66	19.28	40.03
	King–Reg–Low	53,792	111,663	25	2,151.67	4,466.52
	King–Reg–Med	80,076	166,225	45	1,779.47	3,693.89
	King–Reg–High	140,825	292,329	111	1,268.69	2,633.59
	King–Over–Low	28,075	58,279	66	425.38	883.02
	King–Over–Med	15,392	31,952	69	223.08	463.07
	King–Over–High	34,531	71,680	70	493.29	1,024.00
	Pierce–Reg–Low	47,115	97,803	68	692.87	1,438.28
2019	**Pierce–Reg–Med**	53,725	111,524	78	688.78	1,429.79
	Pierce–Reg–High	19,735	40,966	102	193.48	401.63
	Pierce–Over–Low	27,225	56,515	147	185.21	384.46
	Pierce–Over–Med	5,243	10,883	12	436.89	906.92
	Snohomish–Reg–Low	36,565	75,902	53	689.90	1,432.11
	Snohomish–Reg–Med	55,608	115,433	75	741.44	1,539.11
	Snohomish–Reg–High	32,293	67,036	65	496.82	1,031.32
	Snohomish–Over–Low	11,716	24,320	33	355.02	736.97
	Snohomish–Over–Med	3,394	7,046	37	91.74	190.43
	Kitsap–Reg–Low	15,538	32,255	22	706.29	1,466.14
	Kitsap–Reg–Med	18,011	37,387	38	473.96	983.87
	Kitsap–Reg–High	4,883	10,137	29	168.39	349.55
	Kitsap–Over–Low	5,340	11,085	34	157.06	326.03
	Kitsap–Over–Med	5,180	10,753	30	172.67	358.43

Source: RSG

REWEIGHTING TO ACCOUNT FOR NONRESPONSE BIAS

The 2018 ACS PUMS data served as the target data for weighting these datasets. An IPF algorithm was used to adjust the initial weights so that the sum of the weights matched various household-level and person-level marginal targets within each of the defined weighting geographies. The IPF routine was seeded with the initial expansion weights. Then, the algorithm was completed in a way to minimize deviation from the initial weights while matching the control targets as closely as possible.

WEIGHTING GEOGRAPHY

Using ACS PUMS data, separate sets of weighting controls were generated for each of the Public Use Microdata Areas (PUMAs) in study areas. (PUMAs have populations in the range of 100,000–200,000). As survey sample sizes are often too sparse to weight to all distributions within each PUMA, another option is to use county-level targets instead (unless the counties are smaller than PUMAs, in which case PUMAs would be used). However, there can be a wide variation in the level of urbanization across PUMAs within a county.

This weighting process used the following geographies for weighting to match what was done in 2017:

- King County–Seattle: Downtown (PUMA: 11603)
- King County–Seattle: North (PUMAs: 11601, 11602)
- King County–Redmond (PUMAs: 11607, 11616)
- King County–Seattle: Capitol/Duwamish & Beacon Hill (PUMAs: 11604, 11605)
- King County–Other (PUMAs: 11606, 11608, 11609, 11610, 11611, 11612, 11613, 11614, 11615)
- Pierce + Kitsap Counties (PUMAs: 11501, 11502, 11503, 11504, 11505, 11506, 11507, 11801, 11802)
- Snohomish County (PUMAs: 11701, 11702, 11703, 11704, 11705, 11706)

HOUSEHOLD AND PERSON-WEIGHTING TARGETS

Several person-level and household-level target categories exist. The person-level targets are designed to identify the person types that are typically used in activity-based modeling software such as CT-RAMP and DaySim. The weighting targets were derived from PUMS data using the person-level weights. PUMS allows definition of full-time vs. part-time workers in a way

consistent with the survey, while ACS tables do not provide consistent information. (For example, in the ACS tables, “part-time” includes people who only worked part of the previous year.) The PUMA geography identified in the PUMS data is sufficient for setting weighting targets, even using the latest one-year PUMS (2018). Table 31 and Table 32 provide the household-level and person-level variables used in the IPF exercise.

TABLE 31: HOUSEHOLD-LEVEL TARGET VARIABLES

VARIABLE	VALUES
Household Size	1-person 2-person 3-person 4-person 5-person or more
Household Income ***(Imputed if nonresponse)***	Under $25,000 $25,000–$49,000 $50,000–$74,000 $75,000–$99,000 $100,000–$149,000 $150,000 or more
Household Workers	0 workers 1 worker 2 workers 3 workers or more
Household Vehicles	0 vehicles 1 vehicle 2 vehicles 3 vehicles or more
Age of Head of Household	Under 35 years 35–64 years 65 years or older
Household Kids	0 kids 1 or more kids
Total Households	–

TABLE 32: PERSON-LEVEL TARGET VARIABLES

VARIABLE	VALUES
Person Gender (Imputed if nonresponse)	Male Female
Person Age	Under 5 years 5–15 years 16–17 years 18–24 years 25–44 years 45–64 years 65 years or older
Person Worker Status	Worker Nonworker
Person University Student Status	University student Nonuniversity student
Person Race *(Imputed if nonresponse)*	White only Asian / Pacific Islander only Other
Person Typical Commute Mode	Works from home Transit Walk/Bike Car (drive alone) Other No commute
Total Persons	–

IMPUTATION OF MISSING VALUES

The income, gender, and race questions in the survey allowed participants to respond with "prefer not to answer." To facilitate data weighting, RSG imputed missing values for these variables.

Income

RSG imputed income using a model-based approach where missing income was predicted based on a set of independent variables such as the following:

- Income distribution of the block group (BG).
- Number of working adults in the household.
- Educational attainment of the household.
- Number of children in the household.
- Age of the primary survey respondent.
- Homeownership.

- Single-family home residence type.

This model has been tested across many travel survey projects and adequately matches the income values that were reported, indicating it is reliable to predict the missing income values. An assignment of imputed income was made based on the predicted probabilities generated by the imputation model.

Model specification and coefficients are shown in Table 33.

TABLE 33: INCOME IMPUTATION MODEL SUMMARY

PARAMETER	DESCRIPTION	ESTIMATE	STD ERROR	T-STATISTIC
I(finc_0k_25k + finc_25k_50k + finc_50k_75k)	Fraction of people in BG with incomes 0k-75k	-0.819	0.387	-2.119
finc_100k_150k	Fraction of people in BG with incomes 100k-150k	1.055	0.526	2.006
finc_150k_plus	Fraction of people in BG with incomes more than 150k	2.142	0.413	5.181
nonworking_adult_n	Number of nonworking adults in household	0.351	0.053	6.621
child_n	Number of children in household	0.098	0.040	2.434
full_time_graduate_degree_n	Number of full- time workers with graduate degrees in household	1.971	0.064	30.731
part_time_graduate_degree_n	Number of part- time workers with graduate degrees in household	0.579	0.137	4.232
full_time_bachelor_degree_n	Number of full- time workers with bachelor's degrees in household	1.703	0.060	28.239
part_time_bachelor_degree_n	Number of part- time workers with bachelor's degrees in household	0.205	0.106	1.928
full_time_low_education_n	Number of full-time workers with no advanced degrees in household	0.883	0.061	14.377
part_time_low_education_n	Number of part-time workers with no advanced degrees in household	-0.086	0.103	-0.836
head_under_35_n	Head of household under 35 years	-0.070	0.059	-1.192
head_over_65_n	Head of household over 65 years	0.017	0.083	0.204
own_home	Household owns home	1.174	0.063	18.520
single_family_home	Household lives in single-family home	0.024	0.067	0.355

McFadden's rho-squared: 0.15
Source: RSG

Gender

Missing gender was probabilistically assigned based on the sample data's gender distribution within the respondent's age category.

Ethnicity

Ethnicity was also imputed using a model-based approach. In this case, two models were used depending on what was known about the respondent's household. In households where ethnicity was known for at least one adult, ethnicity was imputed using the model below (Table 34), which depended on the percentage of the households with that ethnic characteristic. For households where ethnicity was not known for any adults, a more general model was used, which is described in Table 35.

TABLE 34: ETHNICITY IMPUTATION MODEL FOR HOUSEHOLDS WITH AT LEAST ONE ADULT REPORTING ETHNICITY

ALTERNATIVE	PARAMETER	DESCRIPTION	ESTIMATE	STD ERROR	T-STATISTIC	P-VALUE
Asian/PI	(Intercept)	–	-0.525	0.289	-1.813	0.070
	perc_race_white	% of HH who is white	-8.123	0.574	-14.143	0.000
	perc_race_api	% of HH who is Asian/PI	9.221	0.498	18.526	0.000
	perc_race_other	% of HH who is other	-2.590	1.064	-2.435	0.015
Other	(Intercept)	–	-1.044	0.352	-2.963	0.003
	perc_race_white	% of HH who is white	-7.116	0.623	-11.428	0.000
	perc_race_api	% of HH who is Asian/PI	-1.900	1.042	-1.823	0.068
	perc_race_other	% of HH who is other	9.562	0.523	18.280	0.000

McFadden's rho-squared: 0.845
Source: RSG

TABLE 35: ETHNICITY IMPUTATION MODEL FOR HOUSEHOLDS WITH NO ADULTS REPORTING ETHNICITY

ALTERNATIVE	PARAMETER	DESCRIPTION	ESTIMATE	STD ERROR	T-STATISTIC	P-VALUE
Asian/PI	(Intercept)	–	-0.665	0.093	-7.161	0.000
	frace_white_only	Fraction of people in BG who are white	-1.706	0.102	-16.669	0.000
	frace_api_only	Fraction of people in BG who are Asian/PI	2.074	0.141	14.753	0.000
	frace_other	Fraction of people in BG who are other	-1.033	0.176	-5.880	0.000
	factor(college_educated)1	Has Associate Degree	0.050	0.160	0.314	0.753
	factor(college_educated)2	Has Bachelor Degree	0.474	0.092	5.177	0.000
	factor(college_educated)3	Has Master/PhD	0.620	0.095	6.525	0.000
	factor(employed)1	Employed part time	0.074	0.114	0.644	0.520
	factor(employed)2	Employed full-time	0.169	0.071	2.389	0.017
	factor(num_people_cat)2	HH size = 2	0.182	0.080	2.280	0.023
	factor(num_people_cat)3	HH size = 3	0.636	0.104	6.095	0.000
	factor(num_people_cat)4	HH size = 4	1.149	0.113	10.167	0.000
	factor(num_people_cat)5	HH size = 5+	0.859	0.190	4.526	0.000
	own_home	Owns home	0.019	0.075	0.254	0.800
	single_family_home	Lives in a single-family home	-0.499	0.082	-6.076	0.000
	is_student	Is a student (adult only)	0.412	0.101	4.065	0.000
	factor(has_license)1	Has a driver license	-0.725	0.103	-7.039	0.000
	hh_imputation_1	Income less than $25k	-0.186	0.101	-1.844	0.065
	hh_imputation_2	Income between $25k and $50k	-0.118	0.078	-1.500	0.134
	hh_imputation_3	Income between $50k and $75k	-0.216	0.077	-2.811	0.005
	hh_imputation_4	Income between $75k and $100k	-0.121	0.079	-1.544	0.123
	hh_imputation_5	Income between $100k and $150k	-0.044	0.068	-0.650	0.515
	hh_imputation_6	Income greater than $150k	0.019	0.073	0.266	0.790
Other	(Intercept)	–	-0.768	0.112	-6.857	0.000
	frace_white_only	Fraction of people in BG who are white	-1.266	0.133	-9.548	0.000
	frace_api_only	Fraction of people in BG who are Asian/PI	-0.124	0.215	-0.576	0.565

ALTERNATIVE	PARAMETER	DESCRIPTION	ESTIMATE	STD ERROR	T-STATISTIC	P-VALUE
	frace_other	Fraction of people in BG who are other	0.621	0.215	2.888	0.004
	factor(college_educated)1	Has Associate Degree	0.061	0.157	0.386	0.699
	factor(college_educated)2	Has Bachelor Degree	-0.422	0.106	-3.975	0.000
	factor(college_educated)3	Has Master/PhD	-0.483	0.119	-4.040	0.000
	factor(employed)1	Employed part time	0.191	0.149	1.282	0.200
	factor(employed)2	Employed full-time	0.357	0.099	3.593	0.000
	factor(num_people_cat)2	HH size = 2	0.092	0.106	0.866	0.386
	factor(num_people_cat)3	HH size = 3	0.765	0.133	5.730	0.000
	factor(num_people_cat)4	HH size = 4	0.426	0.176	2.414	0.016
	factor(num_people_cat)5	HH size = 5+	1.117	0.215	5.192	0.000
	own_home	Owns home	-0.392	0.108	-3.617	0.000
	single_family_home	Lives in a single-family home	-0.266	0.116	-2.287	0.022
	is_student	Is a student (adult only)	0.170	0.140	1.220	0.222
	factor(has_license)1	Has a driver license	-0.689	0.124	-5.575	0.000
	hh_imputation_1	Income less than $25k	0.123	0.114	1.083	0.279
	hh_imputation_2	Income between $25k and $50k	0.079	0.091	0.866	0.386
	hh_imputation_3	Income between $50k and $75k	0.032	0.090	0.358	0.720
	hh_imputation_4	Income between $75k and $100k	-0.335	0.113	-2.975	0.003
	hh_imputation_5	Income between $100k and $150k	-0.215	0.096	-2.237	0.025
	hh_imputation_6	Income greater than $150k	-0.452	0.114	-3.969	0.000

McFadden's rho-squared: 0.087
Source: RSG

EXPANSION OF HOUSEHOLD AND PERSON DATA

The following tables summarize the calculated weights for the two samples (Table 36 and Table 37). These tables provide the distribution of weights that are calculated for each weighting geography.

Table 38 and Table 39 summarize the ratio of the final weight against the initial expansion factor (the weight derived based on the probability of being sampled). In the weighting process, the ratio of the final weight to the initial weight was constrained to be in the range of 0.25 to 5.0 for each household. Allowing the weights to be outside this range would enable the process to match the ACS PUMS targets more exactly, but at the cost of having more extremely high or low weights and the introduction of more variance. Considering that the PUMS targets are estimates based on census survey data, it is not good practice to try to match the targets too precisely at the expense of allowing the survey weights to vary too widely. The range of 0.25 to 5.0 was arrived at after testing alternative limits and judging the best trade-off between accuracy and variability. With these weights, the ratios are near one, which suggests that the final weights (on average) have not deviated significantly from the initial expansion factors.

TABLE 36: SUMMARY STATISTICS OF THE FINAL WEIGHTS (2017 + 2019)

WEIGHTING GEOGRAPHY	MIN	MEAN	MEDIAN	MAX
King County–Redmond	2.192	155.883	25.031	3813.315
King County–Seattle: Capitol/Duwamish & Beacon Hill	2.190	95.611	23.395	5392.274
King County–Seattle: Downtown	2.833	67.508	37.839	2145.618
Pierce + Kitsap Counties	23.551	547.894	375.832	4131.421
King County–Seattle: North	2.672	89.322	23.979	4386.678
King County–Other	4.633	1031.856	765.833	8143.114
Snohomish County	21.581	725.157	593.511	4630.829

Source: RSG

TABLE 37: SUMMARY STATISTICS OF THE FINAL WEIGHTS (2019 ONLY)

WEIGHTING GEOGRAPHY	MIN	MEAN	MEDIAN	MAX
King County–Seattle: Downtown	7.359	122.828	68.821	2372.830
Snohomish County	52.932	1141.502	783.399	7460.200
King County–Seattle: North	5.822	194.931	50.397	4204.973
King County–Other	7.984	2582.538	1636.233	17910.628
King County–Seattle: Capitol/Duwamish & Beacon Hill	4.613	191.695	45.097	5265.665
Pierce + Kitsap Counties	47.723	777.656	540.898	3875.004
King County–Redmond	39.282	2559.691	926.970	8251.581

Source: RSG

TABLE 38: SUMMARY STATISTICS FOR THE RATIO OF FINAL TO INITIAL WEIGHTS (2017 + 2019)

WEIGHTING GEOGRAPHY	MIN	MEAN	MEDIAN	MAX
King County–Redmond	0.323	1.240	0.806	5.000
King County–Seattle: Capitol/Duwamish & Beacon Hill	0.257	0.894	0.625	5.000
King County–Seattle: Downtown	0.250	1.151	0.898	5.000
Pierce + Kitsap Counties	0.368	1.076	0.777	3.738
King County–Seattle: North	0.351	0.936	0.690	4.805
King County–Other	0.354	1.145	0.787	4.003
Snohomish County	0.457	1.105	0.848	5.000

Source: RSG

TABLE 39: SUMMARY STATISTICS FOR THE RATIO OF FINAL TO INITIAL WEIGHTS (2019 ONLY)

WEIGHTING GEOGRAPHY	MIN	MEAN	MEDIAN	MAX
King County–Seattle: Downtown	0.426	1.208	0.795	5.000
Snohomish County	0.252	1.066	0.715	5.000
King County–Seattle: North	0.260	1.097	0.570	5.000
King County–Other	0.256	1.324	0.794	5.000
King County–Seattle: Capitol/Duwamish & Beacon Hill	0.264	0.933	0.564	5.000
Pierce + Kitsap Counties	0.355	1.028	0.800	3.487
King County–Redmond	0.251	1.588	0.782	5.000

Source: RSG

FINAL HOUSEHOLD AND PERSON WEIGHTS

The final weights are effective in facilitating close matches to the regional totals for people, households, persons-in-households, and vehicles-in-households when using this dataset. The expanded and weighted survey values match the targets well, with nearly all household categories matching perfectly (apart from the worker distribution in the Capitol/Duwamish & Beacon Hill geography) and a majority of person categories within 5% (except for the typical commute mode to work) while keeping the weights relatively constrained. (Table 47 and Table 48, in a later section, compare the resulting weights and the targets.) Matching the survey data to the target data even more closely can be achieved by relaxing the constraints on the ratio of the final to initial weights. However, this introduces more variance in the final weights and thereby increases the statistical error in any estimates. Allowing for more extreme weights also increases the likelihood of travel behavior analyses being impacted by extreme or outlier weights, which could unknowingly bias an estimate. This project was conducted at the household-level, so priority was given to matching the household targets. As noted above, the PUMS targets are in fact just estimates themselves, so matching the targets perfectly at the expense of increased statistical error is generally not recommended. Underlying, fundamental issues with the consistency of the household and person-level data from the ACS and PUMS data that can be addressed, which are discussed later in this memo.

CREATING DAY WEIGHTS WITH MULTIDAY SURVEY DATA

With the shift to data collection using smartphone applications such as rMove™, it has become cost effective to capture multiple days of data for each respondent. The question then is how to combine the multiday smartphone-based data with the single-day data from online and call center participants using a consistent weighting method.

RSG's usual approach to create an "average weekday" day-level weight for multi-day smartphone data has been as follows:

- Weight to regional targets to obtain the household- and person-level weights for the included respondents.
- Define weekdays as Monday through Thursday as discussed previously.
- For each respondent, count the number of weekdays (N) for which the respondent provided complete and valid data. Set the person-day-level weight equal to the person-level weight divided by N. In this way, when the data is weighted and aggregated, the sum of the person-day weights across days for each person is equal to the person weight, and the weighted results will reflect an average day for each respondent.

This method results in an "average weekday" for each respondent regardless of the number of days of data provided making the multiday smartphone-based data compatible with the single-day online and call center-based data.

ADJUSTING FOR NONRESPONSE BIAS IN DAY-PATTERN AND TRIP RATES

Previous surveys have revealed that the trip rates from the smartphone-based survey data are 15–20% higher than those from online and call center-based survey data. This finding can be attributed to three main causes:

- Smartphone-owning households have different sociodemographic characteristics than nonsmartphone households and tend to make more trips.
- The online and call center-based data have approximately twice as many "stay-at-home" days with no reported trips when compared to the smartphone-based data.
- Even on days with one or more reported trips, there are more trips per day reported on average in the smartphone-based data than in the online and call center-based data.

All three of these factors are interrelated and need to be isolated from each other through careful analysis and a series of weighting adjustments, as described in the sections below.

A typical method for adjusting the trip rates for online data to match smartphone-based data is to adjust the weights at the trip level. However, RSG employs a two-stage approach, first adjusting weights at the person-day level to adjust for biases in day-pattern types, and then a second stage to adjust weights at the trip level. This is done for two reasons:

1. First, as noted above, one of the key reasons that trip rates are different between the methods is the higher proportion of “stay at home” days with no trips reported in the online diary-based data. While some of this difference is likely legitimate due to differences in demographics, some of it is also likely due to so-called “soft refusal,” whereby it is easy for respondents using the online diary recall method to state that they did not make any trips when in fact they did. It is important to identify the extent of such bias and correct for it at the person-day level, because the “stay at home” cases have no trip records in the data, so the correction cannot be made by factoring weights at the trip level.
2. Second, most activity-based models include a model component to predict the day-pattern type, e.g. stay at home, make mandatory (work or school) trips (and possibly other trips), or make nonmandatory trips only. If the data is used to calibrate such a model at the person-day and household-day levels, it is important to correct any biases that distort the day-pattern types in the data.

DAY-PATTERN ADJUSTMENTS

RSG has developed a method for identifying biases in day-patterns and adjusting for them in the weighting process. The following steps were taken to adjust for biases in day-patterns:

1. A multinomial choice model was estimated at the person-day level. There were three day-pattern choices that were modeled: (1) participant made no trips, (2) participant made mandatory (work or school) trips (and possibly other trips) and (3) participant made nonmandatory trips only. The model included the following variables as independent variables:
   - Income
   - Presence of vehicles in the household
   - Worker status
   - Student status
   - Age

   The model also included an additional bias variable for online diary data and adults proxied via smartphone that captures the trip reporting bias after accounting for the variables listed above.

   The day-pattern model specification and coefficients are shown in Table 40.

TABLE 40: DAY-PATTERN MODEL SUMMARY

ALTERNATIVE	PARAMETER	DESCRIPTION	ESTIMATE	STD ERROR	T-STATISTIC	P-VALUE
Makes mandatory trips	(Intercept)		-2.642	0.154	-17.126	0.000
	online_data	Online diary data	0.293	0.090	3.256	0.001
	zero_vehicle	No vehicles in household	-0.619	0.098	-6.301	0.000
	income_aggregate2	Income 25k-50k	0.387	0.105	3.670	0.000
	income_aggregate3	Income 50k-75k	0.519	0.104	4.987	0.000
	income_aggregate4	Income 75k-100k	0.804	0.111	7.251	0.000
	income_aggregate5	Income > 100k	0.947	0.095	10.002	0.000
	income_aggregate6	Prefer not to answer income	0.424	0.113	3.744	0.000
	age_under_35	Age < 35 years	0.863	0.150	5.745	0.000
	age_35_65	Age between 35-65 years	0.590	0.080	7.392	0.000
	employed	Employed full/part/self	3.344	0.103	32.590	0.000
	is_student	Full or part-time student	-0.122	0.087	-1.402	0.161
	was_proxiedTRUE	Adult proxied	0.586	0.244	2.404	0.016
	online_data:age_under_35	Online diary data x Age	-0.738	0.141	-5.222	0.000
	online_data:was_proxiedTRUE	Online diary data x Proxied	-1.497	0.250	-5.988	0.000
Makes nonmandatory trips only	(Intercept)		1.864	0.124	15.011	0.000
	online_data	Online diary data	-0.044	0.090	-0.491	0.623
	zero_vehicle	No vehicles in household	-0.662	0.102	-6.467	0.000
	income_aggregate2	Income 25k-50k	-0.384	0.103	-3.714	0.000
	income_aggregate3	Income 50k-75k	-0.363	0.104	-3.482	0.000
	income_aggregate4	Income 75k-100k	-0.331	0.112	-2.959	0.003
	income_aggregate5	Income > 100k	-0.111	0.094	-1.191	0.234
	income_aggregate6	Prefer not to answer income	-0.202	0.109	-1.848	0.065
	age_under_35	Age < 35 years	0.302	0.149	2.023	0.043
	age_35_65	Age between 35-65 years	0.208	0.068	3.044	0.002
	employed	Employed full/part/self	-0.733	0.061	-12.028	0.000
	is_student	Full or part-time student	-0.415	0.107	-3.879	0.000
	was_proxiedTRUE	Adult proxied	0.333	0.249	1.337	0.181
	online_data:age_under_35	Online diary data x Age	-0.922	0.150	-6.124	0.000
	online_data:was_proxiedTRUE	Online diary data x Proxied	-1.396	0.255	-5.463	0.000

McFadden's rho-squared: 0.218
Source: RSG

2. The estimated model was applied to each person-day to calculate the probabilities of each of the three-day-pattern alternatives. Then the weighted probabilities were added across the sample within the categories of person-days—(a) those provided by respondents' own smartphones, and (b) those provided by online-diary-based methods or "loaner" phones or via another adult's smartphone by proxy. The aggregate choice shares from applying the model should match the actual choice shares in the data. This provides a check that the model is being applied correctly to the data.
3. Step 2 was repeated, but this time, any bias coefficients in the model were set to zero. None of the bias coefficients apply to smartphone respondents, so the results for this category were unchanged. For the last three categories (online, loaner phone, and proxied participants) the new predictions were what the choice shares would be if any biases did not exist (but all socio-demographic factors still apply). Table 41 shows the percentage of weighted days in each category before and after removing the bias, by household group type and smartphone participation status.

TABLE 41: DAY CATEGORY, BY HOUSEHOLD GROUP & SMARTPHONE PARTICIPATION, WITH AND WITHOUT BIAS REMOVED

HOUSEHOLD GROUP TYPE	SMARTPHONE PARTICIPANT	WITH BIAS			BIAS REMOVED		
		NO-TRAVEL DAYS	MANDATORY TRIP DAYS	NON-MANDATORY TRIP DAYS	NO-TRAVEL DAYS	MANDATORY TRIP DAYS	NON-MANDATORY TRIP DAYS
All adults use own phone	Yes	10%	55%	36%	10%	55%	36%
Online diary	No	17%	51%	32%	9%	51%	40%

Source: RSG

4. The modified aggregate choice predictions (segmented by weighting geography) were added as a new set of targets in the household/person-weighting process described in previous sections. Then the number of person-days for each day-pattern type for each person were counted and used as the corresponding input for weighting at the person-level.
5. The IPF weighting procedure was then rerun with this new added target. The result was that the online households with no trips tended to have their weights reduced, while those with trips (and particularly with nonmandatory trips only) tended to have their weights increased to match the adjusted targets. The weights for smartphone respondents remained essentially unchanged. The advantage of adding these new targets into the household- and person-level weighting process and using all of the targets simultaneously is that all of the household- and person- level weighting targets were still matched as well, which would not be the case if the adjustment was made to the new day-pattern targets in isolation.

TRIP-RATE ADJUSTMENTS

After the first stage of adjustment described above, the new person-day weights were applied to compare the trip rates for the different survey participation methods. Adjusting the weights for day-pattern biases reduced the discrepancy in trip rates between methods, but it did not eliminate it altogether. In practice, the difference in trip rates tends to be higher for nonmandatory trips than for mandatory trips, as respondents are less likely to omit their work and school trips in recall-based diary methods. The differences can also be large for non-home-based trips, since online and by-proxy respondents often tend to omit intermediate stops on multistop tours.

The process for adjusting the trip-level weights was relatively analogous to that described above for day-pattern types but was somewhat simpler. The starting point for the two-stage trip-rate bias correction was the person-day weights. The following steps were then taken to adjust trip rates:

1. Trips were segmented into the following four trip types that have different levels of underreporting. Then for each person-day in the sample, the number of trips were counted by type.
    a. Home-based work/school trips
    b. Home-based other trips
    c. Non-home-based work/school trips
    d. Non-home-based other trips
2. For each trip type, a Poisson regression model was estimated where the dependent variable was the number of trips of that type for the person-day. The independent variables were the same set of household and person variables listed above for the day-pattern models, plus dummy variables for online and call center-based person-days.
3. For each person-day and for each trip type, the estimated regression model was applied with and without the bias coefficients. The ratio of the two estimates resulted in a factor to apply to the trip weight for that person-day. For example, if the model predicted 1.10 trips with the estimated model and 1.32 trips with the bias parameters set to 0 for an online or call center-based person-day, then a factor of 1.32/1.10 = 1.2 was used to multiply the person-day weight to get an adjusted trip weight. For smartphone respondents, the bias coefficients do not apply, so the weight was always 1.0 and the trip weight equaled the person-day weight. A lower bound of 1.0 and an upper bound of 2.0 were placed on ratios to avoid extreme adjustment weights.

The specifications for each of the four regression models are shown in Table 42, Table 43, Table 44, and Table 45. The resulting trip adjustment weights by diary method and trip type are shown in Table 46. Non-home-based trips have rather high adjustment factors for online diary participants, which is likely due to poor recall of intermediate stops between home and another location. As smartphone ownership increases among adults, the need to assign adults to proxy for other adults via smartphone will decrease.

TABLE 42: HOME-BASED WORK TRIP MODEL

PARAMETER	DESCRIPTION	ESTIMATE	STD ERROR	T-STATISTIC	P-VALUE
(Intercept)	–	-2.495	0.059	-42.537	0.000
online_data	Online diary data	0.181	0.022	8.297	0.000
age_under_25	Under age 25	0.265	0.047	5.704	0.000
age_25_45	Age 25 to 45	0.116	0.038	3.042	0.002
age_45_65	Age 45 to 65	0.141	0.038	3.726	0.000
employed_ft	Employed full-time	2.347	0.044	53.452	0.000
employed_pt	Employed part-time	1.965	0.049	39.870	0.000
employed_self	Self-employed	1.529	0.060	25.644	0.000
bachelors	Has bachelor degree	-0.075	0.021	-3.633	0.000
graduate_degree	Has masters/PhD	-0.027	0.022	-1.212	0.225
is_student	Is student	0.474	0.032	14.723	0.000
work_loc_varies	Work location varies	-0.113	0.027	-4.111	0.000
has_kids	HH has children	-0.047	0.019	-2.489	0.013
two_plus_jobs	Works 2+ jobs	0.009	0.034	0.256	0.798
sf_home	Lives in single-family home	-0.017	0.019	-0.849	0.396
has_android_ios	Has Android or iOS	0.168	0.034	4.996	0.000

McFadden's rho-squared: 0.175
Source: RSG

TABLE 43: HOME-BASED OTHER TRIP MODEL

PARAMETER	DESCRIPTION	ESTIMATE	STD ERROR	T-STATISTIC	P-VALUE
(Intercept)	–	0.762	0.027	28.347	0.000
online_data	Online diary data	-0.320	0.015	-21.833	0.000
age_under_25	Under age 25	-0.463	0.038	-12.264	0.000
age_25_45	Age 25 to 45	-0.068	0.020	-3.340	0.001
age_45_65	Age 45 to 65	0.064	0.019	3.441	0.001
employed_ft	Employed full-time	-0.799	0.016	-50.531	0.000
employed_pt	Employed part-time	-0.470	0.024	-19.409	0.000
employed_self	Self-employed	-0.359	0.027	-13.411	0.000
bachelors	Has bachelor degree	0.323	0.015	21.482	0.000
graduate_degree	Has masters/PhD	0.356	0.016	22.534	0.000
is_student	Is student	-0.318	0.030	-10.609	0.000
work_loc_varies	Work location varies	0.162	0.023	7.093	0.000
has_kids	HH has children	0.318	0.014	21.950	0.000
two_plus_jobs	Works 2+ jobs	0.040	0.028	1.443	0.149
sf_home	Lives in single-family home	-0.040	0.015	-2.741	0.006
has_android_ios	Has Android or iOS	0.142	0.020	7.254	0.000

McFadden's rho-squared: 0.08
Source: RSG

TABLE 44: NON-HOME-BASED WORK TRIP MODEL

PARAMETER	DESCRIPTION	ESTIMATE	STD ERROR	T-STATISTIC	P-VALUE
(Intercept)	–	-2.814	0.087	-32.189	0.000
online_data	Online diary data	-0.555	0.023	-23.697	0.000
age_under_25	Under age 25	-0.002	0.057	-0.040	0.968
age_25_45	Age 25 to 45	-0.325	0.045	-7.146	0.000
age_45_65	Age 45 to 65	-0.234	0.045	-5.228	0.000
employed_ft	Employed full-time	2.856	0.071	40.084	0.000
employed_pt	Employed part-time	2.138	0.079	27.021	0.000
employed_self	Self-employed	2.465	0.080	30.820	0.000
bachelors	Has bachelor degree	-0.097	0.026	-3.682	0.000
graduate_degree	Has masters/PhD	0.044	0.027	1.604	0.109
is_student	Is student	-0.028	0.049	-0.584	0.559
work_loc_varies	Work location varies	0.369	0.029	12.886	0.000
has_kids	HH has children	0.087	0.024	3.652	0.000
two_plus_jobs	Works 2+ jobs	0.287	0.036	7.963	0.000
sf_home	Lives in single-family home	-0.167	0.024	-6.876	0.000
has_android_ios	Has Android or iOS	0.445	0.051	8.695	0.000

McFadden's rho-squared: 0.161
Source: RSG

TABLE 45: NON-HOME-BASED OTHER TRIP MODEL

PARAMETER	DESCRIPTION	ESTIMATE	STD ERROR	T-STATISTIC	P-VALUE
(Intercept)	–	0.439	0.042	10.481	0.000
online_data	Online diary data	-0.788	0.022	-35.708	0.000
age_under_25	Under age 25	-0.536	0.061	-8.843	0.000
age_25_45	Age 25 to 45	-0.243	0.032	-7.578	0.000
age_45_65	Age 45 to 65	-0.066	0.029	-2.320	0.020
employed_ft	Employed full-time	-1.124	0.026	-43.247	0.000
employed_pt	Employed part-time	-0.464	0.036	-12.767	0.000
employed_self	Self-employed	-0.575	0.044	-13.207	0.000
bachelors	Has bachelor degree	0.276	0.024	11.756	0.000
graduate_degree	Has masters/PhD	0.161	0.026	6.293	0.000
is_student	Is student	-0.868	0.057	-15.212	0.000
work_loc_varies	Work location varies	0.265	0.037	7.185	0.000
has_kids	HH has children	0.334	0.024	14.121	0.000
two_plus_jobs	Works 2+ jobs	0.268	0.043	6.288	0.000
sf_home	Lives in single-family home	-0.011	0.023	-0.471	0.637
has_android_ios	Has Android or iOS	0.135	0.032	4.250	0.000

McFadden's rho-squared: 0.105
Source: RSG

TABLE 46: TRIP ADJUSTMENT FACTORS

DIARY METHOD	HOME-BASED WORK	HOME-BASED OTHER	NON-HOME-BASED WORK	NON-HOME-BASED OTHER
Smartphone participant	1.00	1.00	1.00	1.00
Online diary	1.00	1.37	1.74	2.00

Source: RSG

FINAL WEIGHTS AND RECOMMENDED USE

The three final weights provided with the dataset are as follows:

- **hh_wt**: The resulting weights from expanding to the PUMS data. This weight should be used for household-level, person-level, and vehicle-level analyses. The sum of the hh_wt in the household and person tables reflects the total number of households and persons in the survey region, respectively.
- **hh_day_wt**: The adjusted day-level weights, which are the hh_wt divided by the number of complete days and adjusted based on the day category (no trips, mandatory trips, or nonmandatory trips only). The sum of the hh_day_wt should match the sum of the hh_wt in the person table.
- **trip_wt**: The resulting adjustment factors from the trip correction process described in the previous sections. This weight is applied at the trip level for any trip-related analysis. This weight is equal to the hh_day_wt multiplied by the adjustment factors described above. The sum of trip_wt in the trip table equals the number of trips taken by residents of the survey region on a “typical day,” as estimated by this survey and weighting approach.

WEIGHTING VALIDATION

TABLE 47: DIFFERENCES BETWEEN HOUSEHOLD WEIGHTED SAMPLE AND TARGET PUMS DATA (2017 + 2019)

VARIABLE	KING COUNTY– OTHER	KING COUNTY– REDMOND	KING COUNTY– SEATTLE: CAPITOL/DUWAMISH & BEACON HILL	KING COUNTY– SEATTLE: DOWNTOWN	KING COUNTY– SEATTLE: NORTH	PIERCE + KITSAP COUNTIES	SNOHOMISH COUNTY
h_income_0k_25k	0	0	2	0	-0	-0	1
h_income_25k_50k	0	0	-1	0	-0	-0	1
h_income_50k_75k	0	0	1	-0	-0	-0	-0
h_income_75k_100k	-0	0	-0	-0	-0	0	1
h_income_100k_150k	-0	0	1	-0	0	0	-2
h_income_150k_plus	-0	-0	-1	-0	0	0	-1
h_size1	-0	-1	13	123	4	-0	-9
h_size2	-0	-1	16	76	3	0	-13
h_size3	0	0	-9	-124	-3	-0	7
h_size4	0	1	-13	-48	-2	-0	10
h_size5plus	0	0	-7	-28	-1	0	5
h_0workers	-0	-0	666	104	1	-0	-4
h_1worker	-0	-0	1,400	193	1	0	3
h_2workers	0	0	1,168	81	-2	0	3
h_3plusworkers	-0	0	-3,234	-379	0	-0	-2
h_0cars	-0	-2,580	26	62	1	0	-1
h_1car	-0	765	-43	27	1	-0	-4
h_2cars	0	1,165	33	-91	-2	0	5
h_3cars_plus	0	650	-15	2	1	-0	1
h_head_under_35	-0	-30	-2	30	1	-0	2
h_head_35_64	0	25	-7	-57	-3	0	5
h_head_over_65	-0	6	9	27	1	-0	-7
h_has_kids	0	0	0	1	-0	0	-0
h_has_no_kids	0	-0	-0	-2	0	-0	0
h_total	0	-0	-0	-0	0	-0	-0
p_male	-6,306	171	-1,965	-3,857	2,962	-8,340	-1,849
p_female	-8,690	1,752	-4,971	2,879	-5,074	14,720	5,262
p_age0_4	11,045	134	4,499	8	2,478	12,366	19,415
p_age5_15	243	5,346	-2,632	693	2,673	4,308	-12,538
p_age16_17	-4,551	-1,350	-1,234	30	-63	7,660	-665
p_age18_24	-22,764	-2,266	-2,216	-2,715	-15,542	-7,478	-17,846
p_age25_44	11,546	-4,368	4,181	93	3,384	-19,588	34,199
p_age45_64	-31,715	3,950	-4,269	2,503	-541	5,265	-22,260
p_age65plus	21,200	477	-5,265	-1,589	5,498	3,846	3,108
p_worker	-7,221	-1,940	-9,230	-1,353	-3,625	-7,776	1,422
p_nonworker	-7,775	3,863	2,294	375	1,512	14,156	1,992
p_univstudent	-1,099	9,348	2,126	-2,570	-4,777	3,746	-7,922
p_not_univstudent	-13,898	-7,425	-9,062	1,592	2,664	2,634	11,335

VARIABLE	KING COUNTY– OTHER	KING COUNTY– REDMOND	KING COUNTY– SEATTLE: CAPITOL/DUWAMISH & BEACON HILL	KING COUNTY– SEATTLE: DOWNTOWN	KING COUNTY– SEATTLE: NORTH	PIERCE + KITSAP COUNTIES	SNOHOMISH COUNTY
p_white	119,524	10,920	16,933	13,030	11,200	41,945	72,118
p_api	17,727	-9,906	-5,759	-6,888	10,947	9,276	-4,346
p_other	-152,247	909	-18,110	-7,121	-24,259	-44,841	-64,359
p_commute_1	9,992	1,149	2,421	4,420	5,471	1,503	14,016
p_commute_2	4,836	-4,471	23,567	20,670	29,772	3,138	21,453
p_commute_3	-28,964	-6,743	2,903	20,275	17,588	-1,426	536
p_commute_4	-22,992	7,542	-29,636	-22,827	-34,073	-13,165	-20,723
p_commute_5	-1,570	3,501	-1,666	-3,523	-3,446	-1,793	-4,929
p_commute_6	234	-1,642	2,098	2,551	1,988	-53	2,610
p_commute_7	23,468	2,587	-6,624	-22,545	-19,414	18,176	-9,550
p_made_no_trips	-1,539	-352	-416	-280	-463	-1,697	-1,160
p_made_mandatory_trips	-7,924	-2,192	-2,251	-1,454	-2,555	-8,349	-6,443
p_made_nonmandatory_only	-6,347	-1,488	-1,634	-912	-1,799	-7,109	-4,809
p_made_not_applicable	6,736	4,130	633	730	5,088	24,335	6,212
p_total	**-14,996**	**1,923**	**-6,936**	**-978**	**-2,113**	**6,380**	**3,413**

Source: RSG

TABLE 48: DIFFERENCES BETWEEN HOUSEHOLD WEIGHTED SAMPLE AND TARGET PUMS DATA (2019 ONLY)

VARIABLE	KING COUNTY– OTHER	KING COUNTY– REDMOND	KING COUNTY– SEATTLE: CAPITOL/DUWAMISH & BEACON HILL	KING COUNTY– SEATTLE: DOWNTOWN	KING COUNTY– SEATTLE: NORTH	PIERCE + KITSAP COUNTIES	SNOHOMISH COUNTY
h_income_0k_25k	-28	-3,689	1	0	1	-0	4
h_income_25k_50k	28	-2,039	-1	0	1	0	5
h_income_50k_75k	17	-545	0	-0	1	0	-4
h_income_75k_100k	-11	-474	0	-0	-0	0	8
h_income_100k_150k	-3	1,878	0	-0	-0	0	-7
h_income_150k_plus	-5	4,842	-1	-0	-2	0	-7
h_size1	218	-3,065	9	609	1,806	0	-28
h_size2	224	1,264	9	375	1,887	0	-47
h_size3	-79	6,050	-5	80	830	0	21
h_size4	-213	3,735	-9	31	566	0	37
h_size5plus	-152	-8,011	-5	-1,094	-5,088	0	17
h_0workers	2,344	-575	1,245	1	924	0	-7
h_1worker	4,705	-534	2,624	1	2,024	0	10
h_2workers	4,047	1,579	2,200	1	1,676	0	-0
h_3plusworkers	-11,099	-497	-6,069	-3	-4,624	0	-3
h_0cars	90	-4,577	32	268	22	0	-1
h_1car	382	-1,080	15	309	34	0	-18
h_2cars	-360	2,676	13	124	-53	0	18
h_3cars_plus	-114	2,954	-60	-701	-2	0	1
h_head_under_35	-10	561	-1	2	-3	0	9
h_head_35_64	-124	1,298	-6	-1	7	0	16

VARIABLE	KING COUNTY– OTHER	KING COUNTY– REDMOND	KING COUNTY– SEATTLE: CAPITOL/DUWAMISH & BEACON HILL	KING COUNTY– SEATTLE: DOWNTOWN	KING COUNTY– SEATTLE: NORTH	PIERCE + KITSAP COUNTIES	SNOHOMISH COUNTY
h_head_over_65	131	-1,887	6	-1	-4	0	-25
h_has_kids	15	-322	0	-0	-1	0	-0
h_has_no_kids	-17	294	-0	0	1	0	0
h_total	-3	-27	-0	-0	-0	0	-0
p_male	17,195	-40	-2,905	-3,582	-7,723	-28,229	13,559
p_female	-35,442	-9,246	-4,046	-721	-9,731	34,683	-15,067
p_age0_4	21,401	-6,274	2,430	3,786	-32	19,984	7,578
p_age5_15	-15,236	6,329	-492	-5,105	-4,223	10,246	1,423
p_age16_17	6,835	-6,845	1,608	258	152	-76	4,750
p_age18_24	-50,226	-2,839	-2,333	-3,988	-19,592	-18,534	-21,790
p_age25_44	23,869	-8,643	-172	635	-4,751	-1,910	32,854
p_age45_64	-15,327	12,117	635	1,659	7,112	-6,498	-23,781
p_age65plus	10,437	-3,132	-8,627	-1,547	3,881	3,242	-2,543
p_worker	-30,632	-809	-13,383	-606	-12,393	-6,462	-10,383
p_nonworker	12,385	-8,477	6,432	-3,696	-5,061	12,916	8,874
p_univstudent	-4,100	17,993	782	-5,779	-6,354	-498	-6,542
p_not_univstudent	-14,147	-27,280	-7,733	1,477	-11,101	6,953	5,034
p_white	249,991	-3,303	22,637	7,540	16,565	51,182	79,670
p_api	-106,065	-32,425	-7,333	-5,563	-9,253	8,929	-14,960
p_other	-162,172	26,441	-22,254	-6,279	-24,766	-53,656	-66,218
p_commute_1	-17,914	-7,023	2,280	2,432	2,365	2,875	2,281
p_commute_2	19,970	9,743	30,246	18,153	42,076	10,400	36,465
p_commute_3	-39,291	-8,073	1,792	22,734	5,026	-2,576	1,873
p_commute_4	-33,039	5,470	-31,694	-22,645	-41,916	-29,043	-28,968
p_commute_5	3,936	2,254	-9,385	-1,009	-2,193	-3,162	-16,676
p_commute_6	-137	-1,841	1,895	2,350	3,059	-282	3,932
p_commute_7	48,229	-9,817	-2,084	-26,317	-25,872	28,242	-416
p_made_no_trips	506	-318	557	-209	233	-1,927	-1,693
p_made_mandatory_trips	-24,561	-517	-7,900	-1,960	-11,714	-8,885	-14,358
p_made_nonmandatory_only	-1,269	-3,486	114	-2,010	514	-12,089	-8,822
p_made_not_applicable	13,000	-6,790	3,546	-1,061	-4,104	30,154	13,752
p_total	**-18,247**	**-9,287**	**-6,951**	**-4,302**	**-17,455**	**6,454**	**-1,508**

Source: RSG

APPENDIX D. MULTIYEAR DATA MEMO

TO: PSRC

FROM: RSG

DATE: February 3, 2020

SUBJECT: Use of Multiple Years of Travel Survey Data in Various Contexts

INTRODUCTION AND BACKGROUND

This memo covers different aspects of merging PSRC household travel survey data from different years in various modeling and planning contexts.

In recent years, RSG has collected household travel survey data for PSRC in four different years:

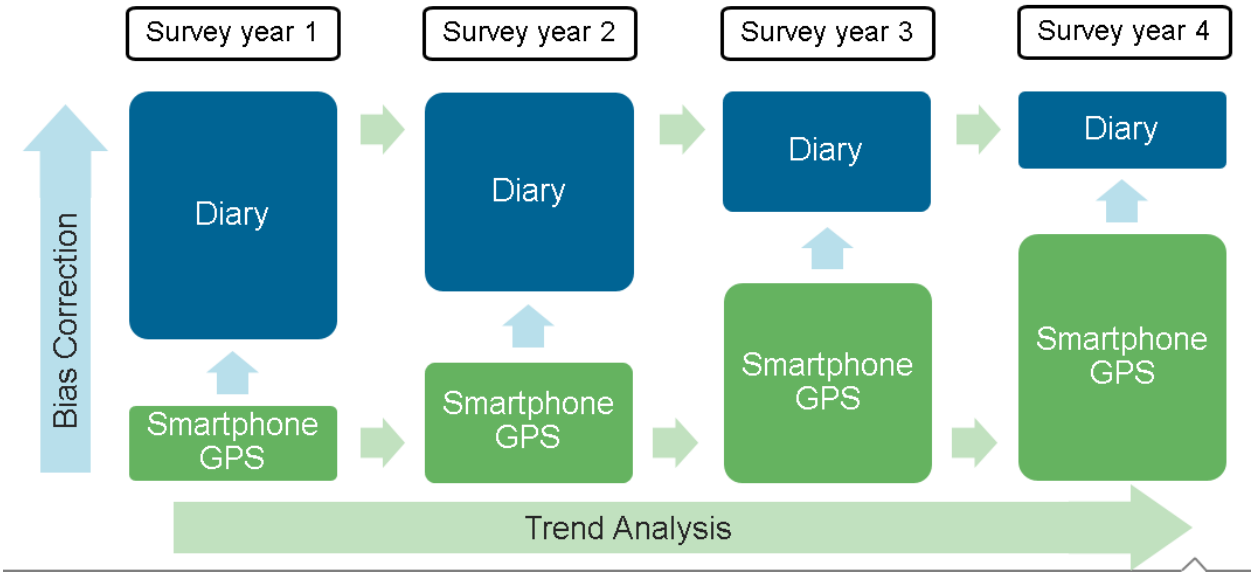
- **2014**: A diary-based household travel survey was carried out, with a sample size of almost 4,000 complete households. Address-based sampling (ABS) was used, with some oversampling in low income areas and low auto ownership areas, as well as in Regional Growth Centers. Both the City of Bellevue and the City of Seattle purchased additional samples for their cities. Seattle's add-on sample targeted households in "Urban Village" (UV) sustainable growth neighborhoods. In the fall, a diary-based person travel survey was carried out among university students and staff from various regional colleges, with the majority from the University of Washington. The main objective was to capture students who live in campus housing (group quarters) or are otherwise unlikely to respond to ABS approaches.
- **2015**: In the spring, a small follow-up household travel survey was done using the same survey instrument as in 2014, including some new respondents and some repeat households from the 2014 sample. In addition, the City of Tacoma contributed additional funds to increase the total number of samples within their jurisdiction. Finally, a small pilot survey was done using an early version of RSG's rMove app for smartphone-based data collection.
- **2017**: A new household travel survey was done using a mix of diary-based and smartphone-based data collection. Households in which all adults owned smartphones were randomly assigned to use the diary-based or the smartphone-based method, with the ability to opt out of using the smartphone-based method. About 21% of households used the smartphone-based option, providing up to seven days of travel data across an

entire week. (The diary-based method continued to collect a single day of data on a Tuesday, Wednesday, or Thursday travel day.) The City of Seattle Urban Village oversample was more substantial than in the 2014 sample, accounting for about half of the 2017 sample. Another sizable oversample was purchased by the City of Redmond, concentrated in their downtown area.

- **2019**: This survey was similar to the 2017 survey, with a similar mix of diary-based and smartphone-based data collection (34% of households using the smartphone-based option), and survey instruments nearly identical to those used in 2017. Once again, the City of Seattle funded a substantial oversample in the UVs. Higher sampling rates were also used in the smaller counties (Kitsap and Snohomish) to obtain a substantial number of respondents in each county.

Another survey is anticipated for 2021 that will use a similar mix of data collection methods and instruments as used in 2017 and 2019. Figure 11 depicts the concept behind the periodic (biannual) survey program, using the smartphone-based data to correct certain types of underreporting biases in the diary-based data, and relying on fairly stable data collection methods within both types across the survey years to facilitate trend analysis.

FIGURE 11: CONCEPTUAL DIAGRAM OF DUAL-METHOD TRAVEL SURVEY DATA COLLECTION



An assumption in the diagram is that the percentage of the sample who participate using the smartphone-based method will increase over time. The percentage of smartphone-based data for the 2021 survey has yet to be decided, and that question will be revisited in the final section of this memo with preliminary recommendations for the 2021 survey.

In the following sections, the memo includes a discussion about how data from different survey years can be used in combination in three important modeling and planning contexts:

1. **Model estimation**: Estimating new parameters for most or all of the variables used in the PSRC SoundCast travel forecasting model system.
2. **Model calibration**: Updating some key parameters and constants in the PSRC SoundCast model (or other models in the region) so that the model predictions match the survey evidence on travel behavior as closely as possible, typically for a single representative "base year."
3. **Trend analysis**: Monitoring year-to-year changes and trends in key travel statistics such as auto ownership, trip generation by purpose, mode shares, and vehicle-miles traveled (VMT) per capita, and being able to relate those changes to key segmentation variables such as income group, age group, and neighborhood (type).

When discussing the merging of multiple years of survey data for these three purposes, it is important to consider various aspects of data collection and processing:

- **The survey methods**: Have there been important changes in the way that the data has been collected? This applies particularly for the rMove smartphone-based method which has been evolving somewhat over its first five years of use.
- **The sampling methods**: Have there been substantial changes in the way that households have been recruited into the surveys? As all of the PSRC surveys to date have relied on ABS, the only changes have been variations in oversampling rates and methods.
- **The weighting methods**: RSG has been a leader in the improvement of data weighting methods to better match both household- and person- level targets in a way that compensates for nonresponse biases and also compensates for oversampling approaches. Recently, RSG has developed new weighting methods that also:
  - Correct for self-selection participation biases that are related to the travel modes that people use most often.
  - Correct for key underreporting biases in the diary-based data as compared to the smartphone-based data—particularly related to nontravel (stay at home) days which are sometimes "soft refusals" in the diary data.
  - Keep the distribution of weights as close as possible to the initial distribution, thus reducing the variance in the weights, which in turn reduces the standard error of weighted statistics.
- **The data processing methods**: Because the smartphone-based data from rMove is a unique mix of "passive data" on time and location trajectories and "active data" on reported purposes, modes, occupancies, etc., it entails processing methods that are

more complex than those used for diary-based data (in which the data collection software itself structures the respondents' reported data to appear logical and internally consistent, for the most part). For rMove data, the respondents' reported trip details can be inconsistent with the background locations, distances, speeds, etc. that are based on the GPS trace information. RSG has been continuously developing and improving data imputation/correction procedures that resolve inconsistencies in the smartphone-based data via series of rules and models to impute trip purposes and modes where necessary. These procedures can also impute answers for missing trip surveys to fill in gaps in travel days and increase the number of complete person-days of data. Because PSRC has done substantial checking and editing of the travel survey data in-house, this type of postprocessing may be less relevant for PSRC than for most other agencies carrying out smartphone-based surveys, although PSRC may choose to rely more on RSG data processing and imputation methods for future surveys. (See the final section of the memo.)

MODEL ESTIMATION

When estimating new coefficients for SoundCast components using household travel survey data, a typical series of steps for PSRC (or any consultants assisting PSRC) includes:

1. Select a base year, which aligns closely with the survey year.
2. Carry out tour and pattern formation logic and format the travel survey data into the file types (household, person, household-day, person-day, tour and trip) and formats used by the DaySim software platform underlying SoundCast.
3. Prepare parcel-based land-use data for that base year, including data on households, employment by sector, enrollment by school type, and parking spaces and prices. That data, along with node-to-node on-street shortest path distances, is used to create distance-decay buffered measures of the data within at least two distance ranges of each parcel. These are key variables in the models, particularly models of location/destination choice.
4. Using a network software suite such as EMME, prepare road and transit networks for the base year, and create "skim matrices" of best-path variables such as travel time (by path component), distance, and cost. These are key variables in mode choice models.
5. Run DaySim in "estimation mode" with the inputs listed above, and this will generate input files for immediate use in the Alogit model estimation software. Note that a similar "estimation mode" capability is planned for the ActivitySim software platform that will eventually replace DaySim.

6. Estimate the models, making any changes in model specification that seem worthwhile, and use the new coefficients for the updated version of the model system (after the calibration step, which is discussed in the next section).

If one wishes to use survey data from two separate survey years (for example) in this estimation process, there are two main options:

1. If the changes in land use or networks are not considered to be substantial enough to necessitate the extra cost of creating and preparing separate land-use data and network skim files both years, then all that is necessary is to merge the survey data from the two years as if they were collected in a single survey. This merge step is best done after each survey has been run through the tour formation and DaySim formatting step (after step 2 above), since the two surveys may not be identical and may need to be processed slightly differently. Steps 3-6 above would be done once for the combined years.
2. If the changes in land use or networks are considered substantial enough to need separate input files for each survey year, then create separate buffered land-use files and network skim matrices for each survey year and run steps 1-5 above separately for each year. Then, merge the two Alogit data files into a single data file, and carry out the actual model estimation step (step 6 above) on the combined file. Note that this process was used to combine data from 13 different travel regions in estimation as part of the Federal Highway Administration activity-based model transferability project carried out by John Bowman and RSG. In the PSRC case, it would be combining data from different years instead of different regions, but the process is similar. It may be useful to add an indicator to the files to indicate which survey year each observation is from, and then it would be possible to test for year-specific differences in some model parameters such as alternative-specific constants.

RSG cannot provide a firm recommendation for either one of the two options above, as it depends on the amount of change that has happened in the background data between the survey years, the availability of staff resources to do the work, and the sufficiency of the sample sizes for estimation using one year of data versus two years of data. In the case of PSRC, the 2017 and 2019 sample sizes are fairly limited outside of the City of Seattle, so there would be a clear benefit in increasing the sample sizes.

If there is new parcel data readily available for each year, then the cost of preparing year-specific parcel inputs may not be too high. On the other hand, if 2019 parcel data is not yet available but there are other indicators of growth rates at the census block or BG level (for example), then factors based on those geographies could be applied to the 2017 parcel data to at least incorporate the largest changes.

For network data, the process is not so clear. It could be as simple as taking the 2017 network and editing the networks to incorporate any major road projects or transit service changes between 2017 and 2019, ignoring more minor changes that may have occurred.

A similar question is whether to merge in the data from the 2014 survey as well. That survey data had a large sample size which would clearly help to estimate parameters more accurately. If that data has already been merged with 2014 land-use and network data and prepared in DaySim format, then merging in the 2014 data for estimation in step 5 above could be useful, although in that case it seems particularly important to use interactions between the survey year and alternative-specific constants, so that unobserved differences in behavior or survey method influences between the years do not get confounded in the estimates of the other model parameters.

These same considerations will also apply in the future to decide if the 2021 data should be merged in estimation with 2019 data or with both 2017 and 2019 data. In general, if the new combined sample size is sufficient that an older year of data (i.e. a survey that was done several years before the new model base year) can be omitted from estimation, then it is probably best to do so. The longer the time range of years combined in estimation, the more important it is to (a) include different background land-use and network variables for at least some of the years (although some adjacent years could share background data), and (b) to include interaction effects between the survey years and the alternative-specific constants, as discussed above.

Changes in survey weighting methods across years is not an issue in model estimation because model estimation is generally done using use unweighted data. Weighting methods are important, however, in model calibration and trend analysis, discussed in later sections.

Biases in data between survey methods can be important to consider in model estimation. Although weighting methods can also adjust for these biases in the calibration process, it is best to also consider them in estimation where possible, to avoid biasing other parameter estimates. Even when using diary-based data only, the DaySim input format has included the “diary” and “proxy” items to flag cases where the person did not use a travel diary to record travel or where an adult’s travel was reported by proxy by another adult. These flags can then be interacted with other survey variables to adjust for biases. Such added variables are probably most important in the day-pattern tour and stop generation models, since the main effect of proxy-based reporting is underreporting of trips and stops, particularly intermediate stops on tours. When combining diary-based and smartphone-based data in estimation, it is advisable to use the “diary” field to flag diary-based data (as opposed to smartphone-based) and to continue to use the “proxy” field to flag adult travel that is reported by proxy (typically only possible with the diary-based method). Children’s travel is reported by proxy in nearly all cases, so it is less important to use these flags for children’s data.

MODEL CALIBRATION

A typical process for model calibration is to run the model system—SoundCast in this case—on the entire regional synthetical population for the base year, and then to compare the model output to weighted, aggregated survey data. This tends to be an iterative process, as the outcome from one model component can affect other model components. Typical measures for calibration include auto ownership distribution by county or district, tour and trip generation rates by purpose, trip length distribution by purpose, trip mode choice by purpose, and trip time of day distribution by purpose. Increasingly, “big data” can be used instead of (or in addition to) weighted survey data to calibrate district-to-district origin-destination (OD) trip distributions, but even big data requires travel survey data for expansion to adjust for trip distance biases. It is not always clear how proprietary OD data vendors such as Streetlight perform such expansion.

In contrast to model estimation, model calibration does not require merging the survey data with network and land-use data, so the issue of having to prepare multiple versions of such data for different survey years is not relevant (unless one wishes to perform separate calibration for different base years only a couple of years apart, which is not common practice).

Also, in contrast to model estimation and application, where the range of error around model predictions is quite complex to determine, calculating the range of error around calibration targets is quite tractable. For example, the standard error for the calibration target for the transit mode share for shopping tours calculated from weighted survey data is mainly a function of the number of shopping tours in the data and the variance of the weights applied to those shopping tours. The higher the sample size and the lower the variance in weights, the tighter is the range of error around the calibration target.

This pertains to the question of whether combining survey years will make calibration more accurate. For example, if the model base year is 2017, should the 2019 data be combined with the 2017 data for calibration? The answer is partly a function of sample size. If the 2017 sample was large enough to provide accurate weighted distributions for all choice dimensions for all market segments and geographic segments, then the 2019 data would not be needed. For PSRC, this is not the case, and the larger sample size obtained from combining the two years will likely increase the accuracy of calibration targets more than using a different year will tend to decrease the accuracy—particularly if one does not expect widely different behavior in the two years. If a major recession or depression had started in 2018, on the other hand, then it could be the case that travel patterns would have changed enough from 2017 to 2019 that adding the 2019 data would hinder more than help the calibration accuracy. (Fortunately, that did not happen in 2018.) As another example, if the new base year is 2018, then using a combination of 2017 and 2019 data may be ideal in giving an average picture of travel patterns in 2018. Since the census control data used for data weighting tends to lag a year behind real

time, and 2018 is the latest ACS data currently available, then the 2019 survey data was weighted to 2018 socio-demographic targets in any case.

Also, in contrast to model estimation, data weighting is important for model calibration. Because DaySim works mainly at the person-day level, RSG considers matching total persons more important than matching total households when the two totals are somewhat inconsistent (which is typically the case with ACS data). Also, DaySim (and CT-RAMP and ActivitySim) uses eight different person types as one of the most important segmentation variables in the models, and person-level weighting targets are selected to give an accurate distribution across those eight person types.

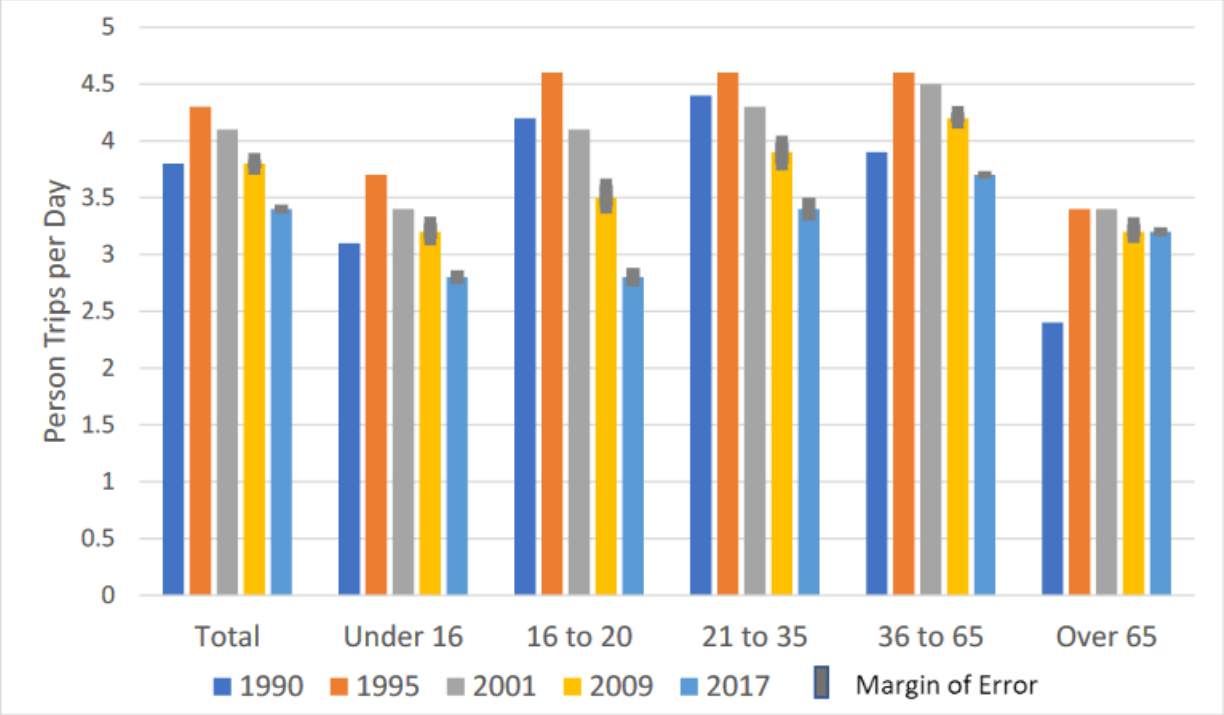
Most importantly, RSG's latest weighting methods use the smartphone-based data to adjust underreporting biases in the diary-based data at both the day-pattern level and the trip level. In the past, predicted trip rates from activity-based models would typically be too low, so that predicted demand would be too low to match actual traffic levels, transit ridership, etc. Common practice in such a case is to assume that the number of "stay at home" days in the data is too high (15 to 20% instead of 10% or so), and that nonmandatory tours in particular have been underreported in the survey. With the smartphone-based data and updated weighting/correction methods, it is possible to get much more accurate calibration targets to begin the calibration process.

RSG's recommendation for model calibration is to use the combined 2017 and 2019 data along with the weights that were derived using the combined data and the 2018 ACS targets.

TREND ANALYSIS

Data weighting is also critical to trend analysis. Any changes in survey methodology or weighting methodology across years can give results that show spurious changes between the years. A survey that is designed primarily for trend analysis is the National Household Travel Survey (NHTS), a repeated cross-sectional national survey carried out every eight years or so. Figure 12 shows that the 2017 NHTS data indicates a decrease in travel since 2009 for all age groups. This result seems questionable—particularly because 2009 was in the midst of a major recession (which was posited at the time as a reason for the indicated decrease in travel in 2009 compared to 2001). In fact, Figure 12 shows the NHTS weighted trips per person decreasing in every survey year since 1995, consistently across all age groups. Because the NHTS surveys are about eight years apart, there tend to be significant changes in sampling methodology (e.g. random digit dialing versus ABS) and survey methodology (e.g. different proportions of respondents using mail, telephone, and online diary responses). It is likely that there have also been substantial changes in data weighting methods over time.

FIGURE 12: SUMMARY OF TRAVEL TRENDS—2017 NHTS



Source: https://nhts.ornl.gov/assets/2017_nhts_summary_travel_trends.pdf

Perhaps most problematic is the decline in respondents' general willingness to answer surveys, in terms of both survey nonresponse and item nonresponse/trip underreporting. As a result, it is not possible to know whether the declining travel indicated by the NHTS data over time is an indication of true behavior or an artifact of increasing trip underreporting or effects of changing survey and weighting methods. Given that other data sources indicate that travel has generally been increasing over time, the NHTS trend results seem suspect. Nevertheless, once one accounts for the overall trend between time periods, it is possible to do some useful analysis on the NHTS data by differentiating the trends over time across different market segments. For example, do millennials show more or less change in trip rates of VMT compared to other age groups? If one can assume that changes in survey methods or weighting methods or travel underreporting affect all age groups equally, then this type of comparative analysis is valid. However, RSG has found consistently across several recent surveys that, compared to smartphone-based data, the trip underreporting in diary-based methods has become most pronounced among the young adult age groups under age 35.

The discussion above highlights some of the inherent difficulties in interpreting trends from survey data collected across multiple years. Fortunately, the PSRC survey data is collected every two years rather than every seven or eight years like the NHTS, and the survey data collection methods have been applied more consistently across years. Referring back to Figure

11, while the PSRC surveys since 2017 have used both smartphone-based and diary-based methods, both methods have remained similar across time.

One thing that has changed over time, however, are the weighting methods applied by RSG, as mentioned in preceding sections. One key suggestion that would improve trend analysis across the 2014/15, 2017, and 2019 surveys would be to apply the same weighting methods to each dataset. This includes both the method for deriving consistent household weights with both household-level and person-level targets, as well as methods for correcting underreporting biases in the diary-based data.

Since the majority of all respondents in each year used the diary-based method, which has remained stable over recent years, it may also be useful to weight the diary-based data alone in each survey year, excluding any smartphone-based data, and using the same weighting method for each year.

One approach for carrying out these extra weighting tasks would be to contract RSG to apply the same weighting method to the dataset for each year, perhaps including an extra weighting for the diary-based data only. An alternative approach would be for RSG to train PSRC in using the open-source PopulationSim software (in the same family of Python-based code as ActivitySim) to do survey weighting. RSG will soon start to use PopulationSim for survey weighting after adapting it to be able to perform all of the different types of weighting steps that are necessary. Compared to RSG's modified iterative proportional fitting (IPF) methods, PopulationSim has a somewhat more optimized method for minimizing the variance in the resulting weights and is also more flexible in the ability to assign different importance levels to matching different weighting control targets.

PRELIMINARY RECOMMENDATIONS FOR THE 2021 SURVEY

Pending available budget, RSG will revise and add to this section following PSRC's review.

The consultant team anticipates recommending an increase in the percentage of the sample using the smartphone-based method. RSG has been improving the data processing and imputation methods for smartphone-based data over time, as well as improving the app itself to better avoid inconsistencies between the GPS trace data and the trip details reported by the respondents. The result is more complete, accurate, and consistent data than what is obtained via diary-based methods. (RSG believes that some of the same reporting inconsistencies that are found in smartphone-based data are also present in diary-based data, but in the diary-based case, there is no passive trace data available to reveal those inconsistencies.)

Another important advantage of the smartphone-based method is the lower marginal cost of collecting additional days of data from the same respondents. Most respondents report different

travel patterns on different days of the week, so that collecting up to a week of data is cost effective in terms of the information gained. While collecting five weekdays of data from one household does not provide quite as much information as collecting one weekday of data from five households (because there is less variation in the background characteristics), the cost per travel day of data is about 75% less in the former case compared to the latter case. RSG has recently completed a research study of the value of multiday data in model estimation and will provide a copy of that research report to PSRC.

RSG
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55 Railroad Row
White River Junction, VT 05001
802.295.4999
www.rsginc.com


White River Junction & Burlington, VT


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