ANALYZING THE EFFECTS OF COVID-19 ON HUMAN MOBILITY AND TRANSIT RIDERSHIP IN THE PACIFIC NORTHWEST

FINAL PROJECT REPORT

by

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16. Abstract

This study investigated the effects of COVID-19 on trip reductions and decreases in transit ridership in the Pacific Northwest region of the United States, encompassing Washington, Oregon, Idaho, and Alaska. By utilizing multiple data sources, we found that work-related trips in the region declined by more than 30 percent since March of 2020. In contrast, after the summer of 2020, there was an evident recovery of non-work-related trips (e.g., trips to parks and grocery stores). Our results also indicated that public transit ridership diminished by 40 to 90 percent by May of 2020, and its recovery remained extremely slow even after reopening of the economy. The results of panel regression analysis further suggested that social vulnerability and health insurance coverage were significant predictors of changes in human mobility. In addition, public-transit ridership was more likely to rebound in areas with relatively high COVID-19 infection rates. We concluded the report by arguing that supporting socially vulnerable communities and the public transit workforce will be critical for combating the detrimental social impacts of COVID-19, especially under the phasing out of travel restrictions and stay-at-home orders.

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List of Abbreviations

CDC:	Centers for Disease Control and Prevention
CSSE:	Center for Systems Science and Engineering
FTA:	Federal Transit Authority
GIS:	Geographic information systems
IPUMS:	Integrated Public Use Microdata Series
NHGIS:	National Historical Geographic Information System
PacTrans:	Pacific Northwest Transportation Consortium
PNW:	Pacific Northwest
PT:	Public transit
UPT:	Unlinked passenger trips
UZA:	Urbanized area
VOMS:	Vehicles operated in maximum service
VRH:	Vehicle revenue hours
VRM:	Vehicle revenue miles

Executive Summary

- The purpose of this research was to analyze mobility changes amid the unprecedented COVID-19 pandemic in 2020, focusing on the Pacific Northwest region.
- Particular attention was paid to the impact of the COVID-19 pandemic on work-related and non-work-related trips and transit ridership.
- We collected data on human mobility changes and transit ridership in the PNW region and its major urbanized areas.
- We found that mobility changes were mainly characterized by fewer trips to workplaces; however, non-work trips appeared to have recovered since the summer of 2020.
- Public transit ridership declined more substantially during the pandemic, and its recovery was slower than general mobility trends.
- The results of panel regression analysis indicated that sociodemographic variables such as social vulnerability and health care coverage were significantly associated with changes in human mobility.
- Public transit agencies are urged to better prepare for the rebound of ridership by assisting with the vaccination of the public transit workforce.
- A geographic information systems (GIS) dashboard was developed to visualize and track COVID-19 in the PNW region in a near real-time manner.

CHAPTER 1. Introduction

As of April 15, 2021, almost 3 million people have died globally from COVID-19, and over half a million people have died in the United States (Dong et al., 2020). The outbreak of the COVID-19 virus has caused an unprecedented disruption for American transportation systems, and important infrastructure such as public transportation has faced even more challenges because of public concerns regarding infection in crowded spaces (Hamidi & Hamidi, 2021). With an emphasis on changes in human mobility and public transit ridership, the purpose of this study was to analyze the effects of the pandemic on travel behaviors in the Pacific Northwest (PNW) region, which consists of Washington, Oregon, Idaho, and Alaska. The region is of particular interest because several cities in the PNW region (e.g., Seattle, Wash.) were the earliest to report COVID-19 cases and adopted severe measures to curtail community transmission (Brough et al. 2020).

Our work drew upon both open-data sources such as the Google Community Mobility Report and conventional data sets from governmental agencies, such as the Federal Transit Administration (FTA). We employed panel regression analysis techniques to quantify the effects of stay-at-home orders and sociodemographic characteristics on travel behaviors. We also built a dashboard to assist in the data collection and COVID-19 visualization in a real-time manner. The report is organized into the following sections: the second chapter comprehensively reviews the literature on human mobility and public transit ridership amid the COVID-19 pandemic, followed by the third chapter in which the data and methods are described in detail. The fourth and the fifth chapters present results, and the report concludes with a brief discussion on policy implications and future directions.

CHAPTER 2. Literature Review

2.1. Mobility Changes amid COVID-19

The research on human mobility amid COVID-19 has been greatly different from transportation studies before the pandemic. This strand of literature has been drawing upon newly available data sets on mobility and travel behavior, such as geolocated mobile device data and ad hoc travel survey data. Most of these newly available data have been gathered directly from mobile devices' GPS signals, making timely analysis of travel behavior possible (Brough et al., 2020; Chen et al., 2021; Gao et al., 2020.; Hamidi & Hamidi, 2021; Hu, Xiong, Liu, et al., 2021a; Hu, Xiong, Yang, et al., 2021; Lou et al., 2020). These geolocated mobile device data comprise aggregated trip records, and the best example is the Google Community Mobility Report (Hamidi & Zandiatashbar, 2021; Hu & Chen, 2021a; Li et al., 2020; Noland, 2021). These county-level data have been widely used to reflect changes in human mobility and determine ways that human mobility can be correlated with both COVID-19 case data and virus effective reproduction rates (Li et al., 2020; Noland, 2021). For example, Noland employed a fixed-effects model to estimate changes in the effective reproduction rate of COVID-19 in relation to six types of mobility change. Results showed that retail, transit, and workplace mobility changes significantly increased with increases in the virus effective reproduction rate, whereas grocery and park mobility showed smaller increases. Conversely, residence mobility was associated with decreases in the effective reproduction rate. Studies also found that the correlation between mobility and case rates was more significant for large central metropolitan areas than rural counties.

Researchers have also created an analytical framework utilizing big data to understand the effectiveness of responding guidelines and other stay-at-home policies. They found that these policies played a limited role in human mobility changes. For example, Brough et al. (2020) used these data in conjunction with King County Metro data to understand the socioeconomic differences in travel behavior in Seattle. They found that residents of more highly educated neighborhoods substituted modes more often. In contrast, less-educated and lower-income people had a harder time working remotely and switching to other travel modes.

In addition to the application of big data, multiple data platforms were developed after the outbreak of COVID-19 in the spring of 2020, including the University of Maryland's COVID-19 Impact Analysis Platform, the C2SMART COVID-19 Data Dashboard, the University of Wisconsin's GeoDS Lab, and Northwestern University's MOBSLab (Hu, Xiong, Yang, et al., 2021). Ad hoc travel surveys were also conducted in the Netherlands, Sweden, Japan, Turkey, and the United States (de Haas et al., 2020; Jenelius & Cebecauer, 2020; Parady et al., 2020; Shakibaei et al., 2021; Shamshiripour et al., 2020). However, one of the first studies to look at the relationship between COVID-19 restrictions and mobility changes was conducted in Wuhan province, China (Fang et al., 2020). It involved a difference in difference (DID) estimation to address the virus's spread in China. Shakibaei (2020) employed a three-phase panel survey to investigate mobility in Istanbul. The survey, which addressed mode choice and trip choice using various socioeconomic factors, confirmed a significant relationship between transit ridership reduction and COVID-19 and reviewed previous research investigating the impacts of the COVID-19 pandemic on travel behavior.

One particular interest to transportation planners is the relationship between the virus's spread and urban form and population density, one of three measures (density, diversity, design) used to describe built environments (Cervero & Kockelman, 1997). Density has often been described as a significant factor in the mortality and spread of the COVID-19 virus, but the relationship between these two variables is poorly understood (Hamidi et al., 2020; Hamidi & Zandiatashbar, 2021). Hamidi et al. (2020) employed structural equation modeling to test this relationship among 913 metropolitan counties in the U.S. and found that the spread of COVID-19 depended on connectivity more than density. Hamidi & Zandiatashbar (2021) measured compact development's impact on mobility changes in 771 metropolitan counties by using multilevel linear modeling. They found significant reductions in essential trips to grocery stores and transit stations for residents in compact areas, but only small reductions in non-essential trips to parks.

2.2. Public Transit Ridership Decline in the Era of COVID-19

Another topic related to human mobility and transportation is the effect of COVID-19 on public transit and non-motorized travel modes (e.g., cycling). Specifically, researchers have examined how the COVID-19 pandemic has affected ridership in large central metropolitan regions such as Chicago and New York City (Hu & Chen, 2021; Noland, 2021; Shakibaei et al., 2021). Some studies have focused more on the changing relationship between bike-sharing and riding public transit during the pandemic (Hu, Xiong, Liu, et al., 2021). For example, Hu et al. (2021) found that bike-sharing was an important substitute for public transit amid the COVID-19 outbreak. The primary source of data about public transit changes was ridership data collected by service providers and reported to local, state, and federal governments. In the United States, the Federal Transit Administration (FTA) collects data on public transit usage. Data from the FTA include information regarding service providers and fare price, transit supply, and route coverage. In addition to the service and supply of public transit, regional geography, the metropolitan economy, socioeconomic demographics, and other transit infrastructure can also explain variation in public ridership, as evidenced by ourreview of the literature (Alam et al., 2018; Noland, 2021; Taylor et al., 2009).

Concerning the impact of COVID-19 on public transit, Hu and Chen (2021) proposed a joint analytical framework to examine the magnitude and impact of independent variables on transit ridership decline resulting from the COVID-19 pandemic. They found that education, income, and race had a significant impact on ridership. In addition, reduced transit services had a disproportionate impact among less-educated, lower-income people and minorities (Hu & Chen, 2021). Specific attention has been paid to the effective reproduction rate and infection rate of COVID-19 within the context of public transit mobility (Hamidi & Hamidi, 2021; Noland, 2021). Hamidi & Hamidi (2021) used a spatial lag model to determine whether subway ridership and other environmental factors such as points of interest were correlated with COVID-19 infection rates in the New York city. They found crowding to be associated with higher infection rates, especially at points of interest. Average household size, race, and socioeconomic factors were also correlated with higher infection rates, but subway ridership was not a statistically significant variable.

CHAPTER 3. Data and Methods

3.1. Human Mobility

Our study integrated both open-data and governmental data sources to examine changes in movement patterns and public transit usage in the Pacific Northwest during February through December of 2020. Travel pattern data were collected from Google's Community Mobility Report platform. Daily percentage changes in trip volume data from February 15, 2020, to December 22, 2020, were obtained for all counties in the PNW region. Google Mobility Data defined the median value of the five weeks between January 3 and February 6, 2020, as the baseline. The six destination types that Google tracks are retail and recreation, grocery and pharmacy, parks, transit stations, workplace, and residential. The data quality depends on the number of observations within a given location and period. There appeared to be a shortage of data for certain types of trips between August 16 and September 9, 2020, outside of large metropolitan areas (see figure 3.1). Data gaps were especially evident in trips to parks and other non-work-related trips, as shown in figure 3.1.

One limitation of Google data is that they do not account for seasonal variations of travel behavior; therefore, changes were determined by using travel behavior in January 2020 as a baseline. Hence, changes in travel behavior in the summer of 2020 need to be interpreted with caution. The data from the Google Community Mobility Report were aggregated into the monthly average change in visits at the state level, daily change in visits at the state level, monthly average change in visits at the county level, and daily change in visits at the county level (see figure 3.1).

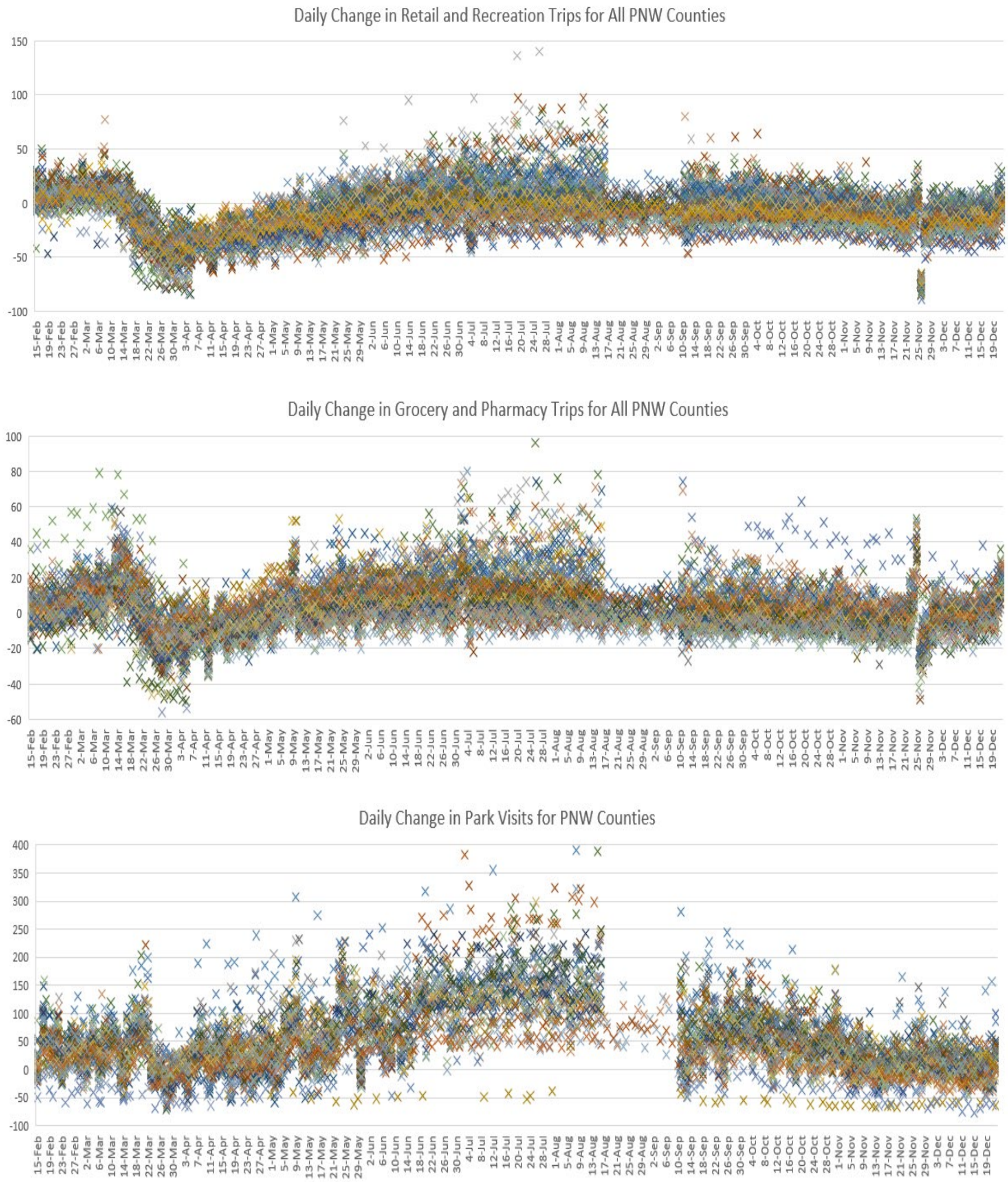

Figure 3-1 Daily average changes in trip visits for six destinations for counties in the PNW

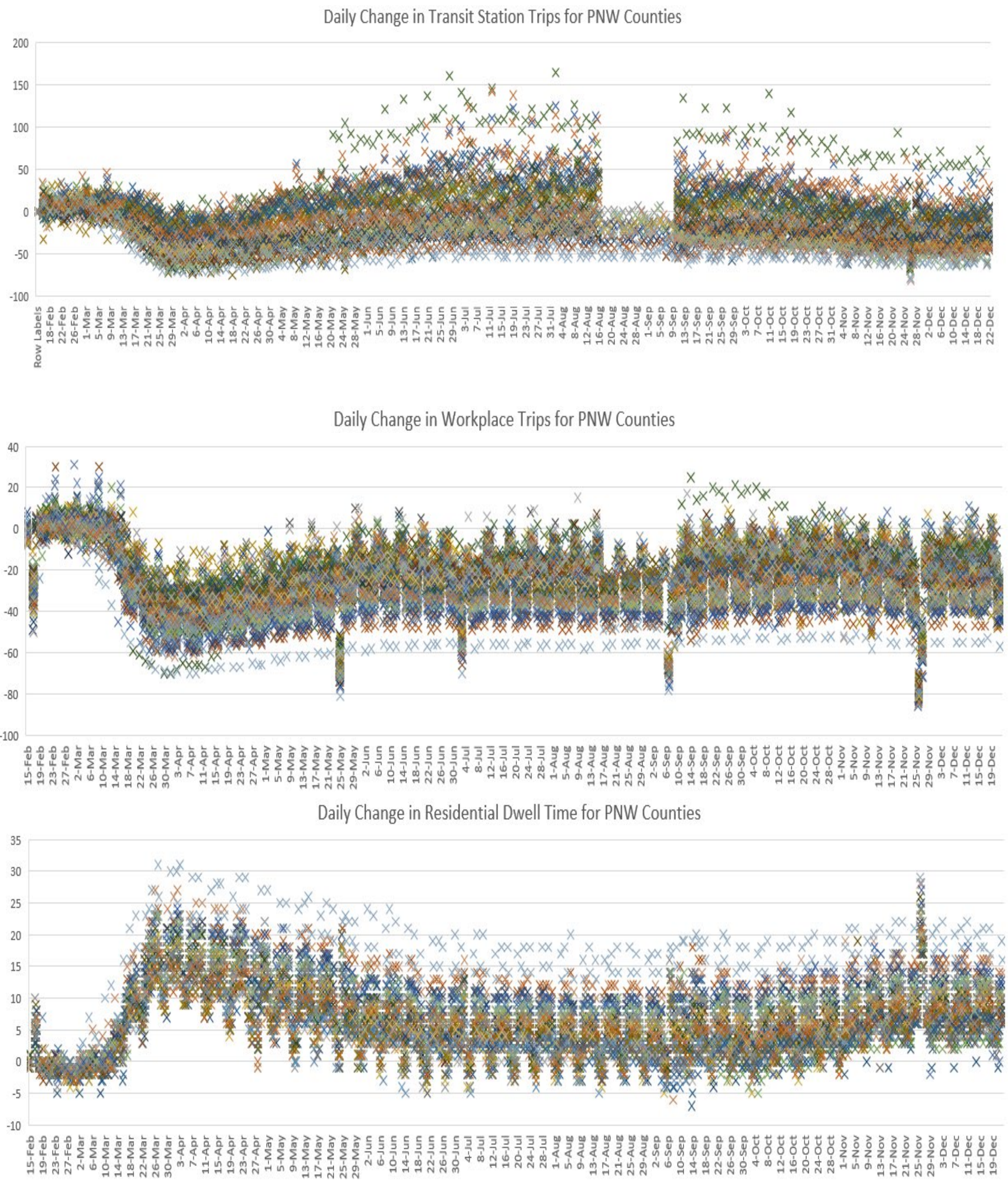

Figure 3.1 (cont.) Daily average changes in trip visits for six destinations for counties in the PNW region

3.2. Public Transit

For the analysis of public transit ridership, the FTA (https://www.transit.dot.gov/ntd/ntd-data) provides key data that are gathered directly from local transit agencies. There are 29 transit agencies in the PNW region, which are located in 16 cities or urban areas (see Appendix B). Monthly ridership data for public transit from January 2002 to September 2020 were obtained from the FTA. We used the raw data set instead of the adjusted data because it contained full reporters' data and was more reliable. These data consisted of one variable describing demand for public transit services and three variables describing the supply of those services. Unlinked passenger trips (UPT) represented the number of transfers made by passengers using a transit mode. This variable was used to estimate public transit (PT) demand. Three variables were used to describe the supply of public transit. Vehicle revenue miles (VRM) was the number of hours that the service operated to collect fares. Vehicle revenue hours (VRH) was the number of miles covered during that service time. Vehicles operated in maximum service (VOMS) was the number of vehicles that operated during a peak season (hourly or seasonal). A summary of the modes provided by transit agencies for 16 urbanized areas is presented in Appendix B. Fixed route bus, demand response, and vanpool were the most common forms of public transit. Articulated bus, cable car, inclined plane, heavy rail, monorail, demand taxi, and Publico were not reported in any urbanized areas in the Pacific Northwest.

Monthly ridership data were categorized according to mode and service type (directly operated or purchased operation). Mode categories were revised in 2012 to describe the bus, light rail, and hybrid rail subcategories present in all urbanized areas, or UZAs. Therefore, data before January of 2012 were excluded from this analysis. Modes were classified into four categories and coded as a new attribute called five models. The first category was bus service, classified as articulated, commuter, fixed route, rapid transit, and trolly. The second category was rail service, classified as Alaska Railroad, cable car, commuter rail, inclined plane, heavy, light, streetcar, monorail, monorail/automated guideway, and hybrid. The third category comprised a pair of nonconventional services relevant to the PNW region: ferry boat, i.e., Washington State Ferries, and Aerial Tramway, i.e., the City of Portland. The final category involved demand-driven services that are not scheduled, classified as demand response, demand taxi, Publico, and vanpool. The total number of UPT, VRH, VRM, and VOMS were calculated according to the five mode categories and were aggregated for each UZA. The percentage change was calculated for each attribute between January and September of 2019 and 2020 by using the following equation:

$$\Delta\, UPT_{month}(\%) = \frac{UPT_{month\_2020} - UPT_{month\_2019}}{UPT_{month\_2019}} * 100$$

3.3. Regression Analysis and Explanatory Variables

We employed panel data regression techniques to model how sociodemographic characteristics and stay-at-home orders affected travel and public transit ridership during the COVID-19 pandemic in the PNW region. Our explanatory variables included the following:

- sociodemographic characteristics
- policy variables such as stay-at-home orders
- variables related to the situation of the pandemic: the numbers of confirmed cases, the numbers of deaths, the death rate, and the infection rate.

Most sociodemographic variables and variables related to the situation of COVID-19 were compiled through the community report portal of the Centers for Disease Control (CDC) (https://beta.healthdata.gov/Health/ COVID-19-Community-Profile-Report/) and other sources such as the American Community Survey (ACS) over the five years of 2014 to 2018.

The American Community Survey collects a wide variety of data on an annual basis at multiple spatial scales. These data can be useful in explaining heterogeneity among public ridership in counties and cities in the Pacific Northwest. The American Community Survey data collected in 2018 were obtained by using the CDC community profile in the United States. Additional GIS data as defined by the 2010 U.S. Census were also gathered from the Integrated Public Use Microdata Series (IPUMS) of the National Historical Geographic Information System (NHGIS) made available through nhgis.org (Manson et al., 2020). Several variables of interest included total population, percent of the population aged 65 or over, poverty rate, percent of the population without health insurance, the average size of households, and two importance composite indexes from the CDC, including the social vulnerability index (SVI) and the COVID-19 community vulnerability index (CCVI). A summary of these variables are presented in table 3-1.

Table 3-1 Summary of sociodemographic variables

Variable	**Field Name**	**Mean (S.D.) UZA/CBSA**	**Mean (S.D.) County**
Natural log of total population (in 10,000 s)	LN_POP	12.82 (0.96)	10.75 (1.35)
% population aged 65 or over	PCT_65	17.00 (0.03)	20.10 (5.96)
% of the population without health insurance	PCT_UNINSURED	8.11 (0.03)	9.85 (4.18)
% of households in poverty	PCT_HOUSE_POV	13.20 (0.03)	14.79 (1.96)
Average household size	AVERAGE_SIZE	2.61 (0.17)	2.56 (0.30)
% of Hispanic population	HISPANIC	0.16 (0.11)	13.86 (11.73)
Social vulnerability index	SVI	0.52 (0.20)	0.54 (0.23)
Community vulnerability index	CCVI	0.38 (0.20)	0.41 (0.23)

Source: CDC and the American Community Survey 2014-2018 (5-year) data; core-based statistical area (CBSA)

Data for the state-level stay-at-home policies were obtained from *The New York Times* to determine when restrictions were put into place and the level of those restrictions. A summary of the stay-at-home orders for the four states in the Pacific Northwest—the declaration date, renewal date, end date, and number of renewal—is presented in table 3-2. The number of months since the issuance of stay-at-home order in each state was used to represent governmental restrictions, following Hamidi and Zandiatashbar (Hamidi & Zandiatashbar, 2021).

Table 3-2 Summary of stay-at-home orders and subsequent renewals

State	Order Type	Declaration Date	Recent Renewal Date	End Date
Alaska	Public Health Emergency	3/9/2020	1/15/2021	4/14/2021
Idaho	State of Emergency	3/13/2020	12/31/2020	1/30/2021
Oregon	State of Emergency	3/8/2020	12/17/2020	3/3/2021
Washington	State of Emergency	2/29/2020	N.A.	N.A.

Two random-effect panel data regression models were used to estimate the relationship between sociodemographics or social vulnerability and mobility changes in general and ridership in particular in the PNW region. The model was estimated twice by using the following equation. One model focused on the reduction in trips to workplaces to indicate mobility change. The other focused on public transit ridership.

$$Y_{it} = \beta_{0t} + \sum \beta_{kit} X_{kit} + u_{it} + \varepsilon_{it}$$

where

- Y_{it} is the dependent variable or the percentage of reduction in trips or ridership in comparison to the baseline period or the same month in the year of 2019 in a county or an urbanized area *i* at month *t*;
- β_{0t} is the intercept value;
- β_{it} represents a vector of parameter value for the independent variable *k* at the county or UZA *I;*
- X_{kit} is the respective independent variable;

- ε_{it} denotes the within-entity error for county or UZA i ;
- u_{it} denotes the between-entity error.

A random-effect model was estimated because the independent or explanatory variables were mostly time-invariant variables (e.g., average household size in a county or a UAZ). By doing so, the error term was not correlated with the predictors, allowing for time-invariant variables to be included as explanatory variables (Torres-Reyna, 2007).

CHAPTER 4. Results

4.1. Changes in Human Mobility

This study examined mobility changes in response to COVID-19 in the PNW region. As shown in figure 4-1, monthly workplace trips (i.e., commuting) decreased for all months in the year of 2020 following February, with the greatest drop of 35 to 40 percent occurring during April 2020. The largest decreases were seen in Washington, followed by Oregon, Idaho, and Alaska. This order remained consistent through October 2020, after which Idaho became the least affected region, with reductions ranging between 15 and 20 percent (see figure 4-2). Monthly average reductions in trips also varied substantially at the county level, with values ranging between -60 percent and 20 percent, depending on the county, between April and September. A dramatic decrease in workplace trips was seen following holidays such as Memorial Day, Independence Day, Labor Day, and Thanksgiving Day, as shown in figure 4-1.

Meanwhile, monthly average residential dwell times increased for all months in 2020 following February, with the greatest increases of 14 percent occurring during April, partly reflecting the impact of stay-at-home orders (figure 4-1). Washington and Oregon experienced larger dwell-time increases than Alaska and Idaho (figure 4-2). Monthly average trips at the county level were variable, with values ranging between -3 percent and 25 pecent in March, April, and October (figure 4-1). A dramatic increase in dwell time was seen during Thanksgiving Day, but not on Memorial Day, Independence Day, or Labor Day.

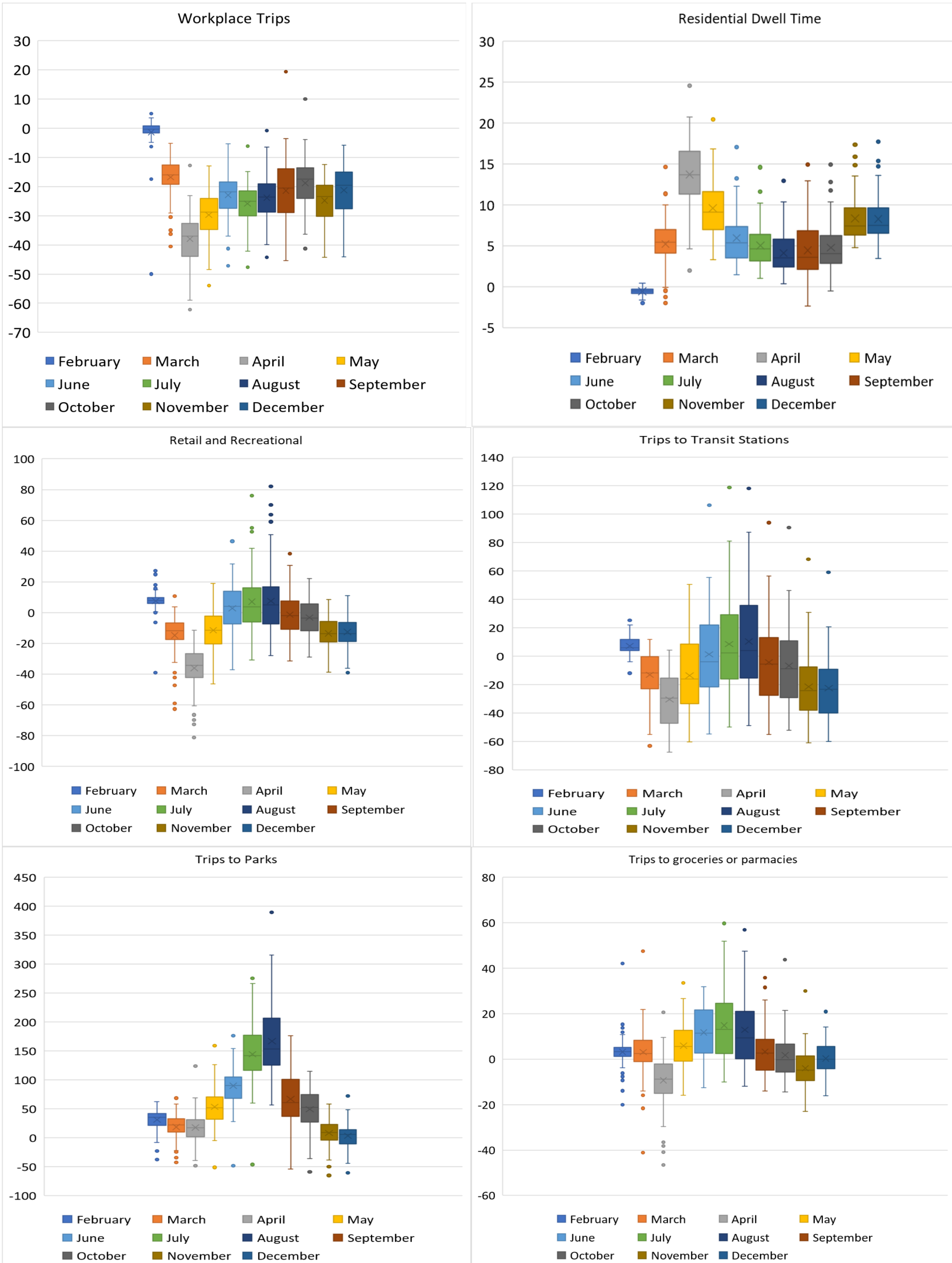

Figure 4-1 Monthly average changes in trip visits for six destinations; relative to the January baseline

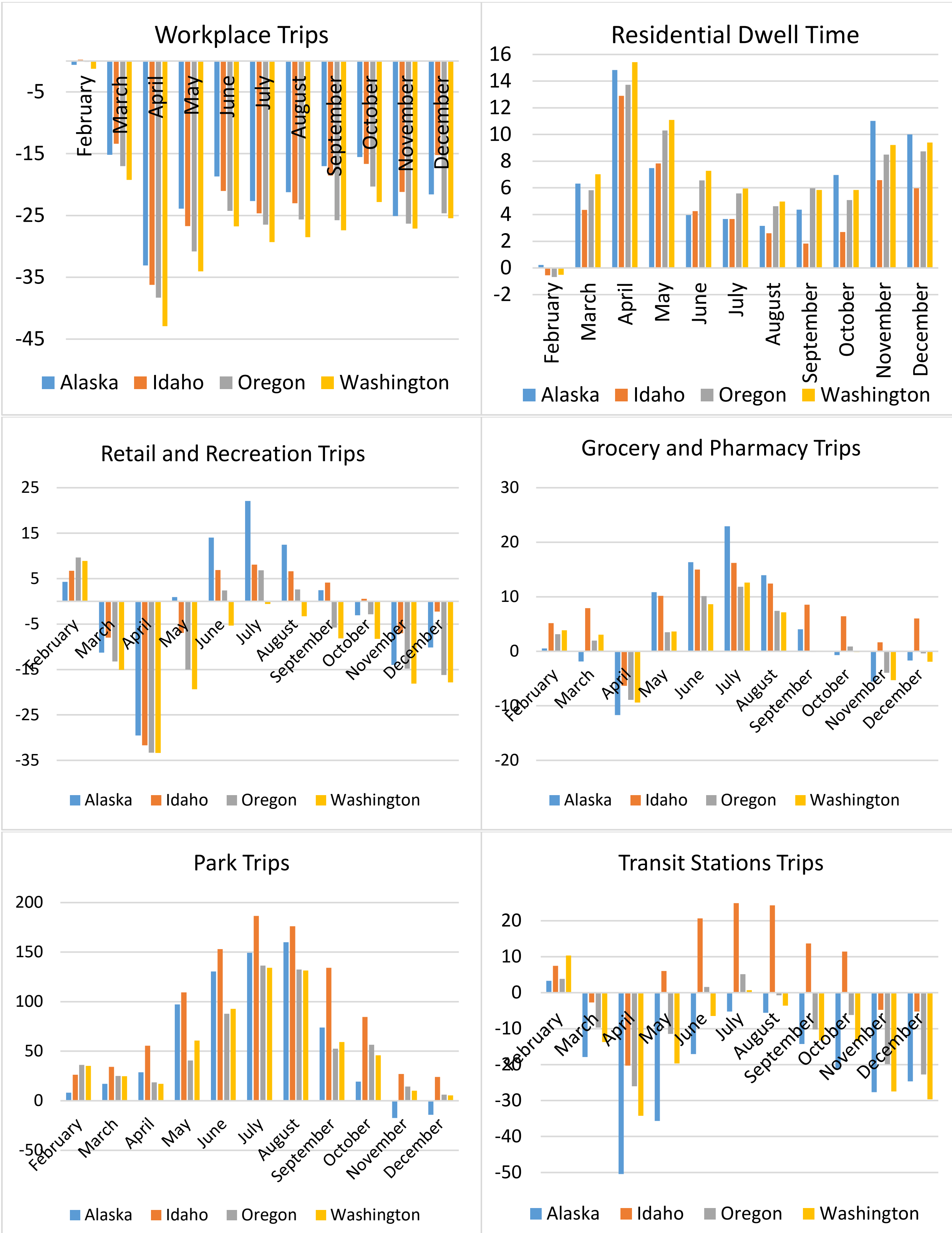

Figure 4-2 Monthly Changes in trips to six destinations in Alaska, Idaho, Oregon, and Washington; relative to the January baseline

Retail and recreation trips decreased by approximately 40 percent in all four states in the PNW between March 22 and April 11, 2020 (figure 4-2). They gradually rose to baseline levels during the summer months of June, July, and August. Trips in Alaska increased by approximately 20 percent during those summer months. These trips at the county level experienced large variability (figure 4-1). Trips decreased by as much as 80 percent in April in comparison to an increase of 80 percent in July and August.

Grocery and pharmacy trips peaked during the first week of March by approximately 30 percent in response to the pandemic before declining sharply by 20 percent during the remaining weeks in March and early April. Trips during the summer months increased by approximately 10 percent during the summer months in all four states. Grocery trips at the county level also experienced great variability (see figure 4-1). In April, trips made for shopping decreased by 40 percent; however, the monthly average shopping trips in July and August increased by as much as 40 percent. Monthly average park visits peaked during the summer months of June, July, and August by over 150 percent, with the greatest increases in Alaska and Idaho. The smallest increases in monthly average park visits occurred in Washington and Oregon. Monthly average trips were above average for all states and areas except Alaska during November and December (figure 4-2).

Changes in monthly average park visits had the most variability of the county level's six destination types. However, at least one PNW county saw a 50 percent decrease in trip visits during each of the months analyzed, whereas the average change in trip visits increased by at least 50 percent on average between May and October. One county in Washington experienced a nearly 400 percent increase in trip visits during August. Monthly average transit station trips decreased during March, April, and May, with the largest decrease of 50 percent occurring during April in Alaska. Idaho started to see an increase in trips in May. This trend continued through October, with trips increasing by at least 20 percent during June, July, and August. Trips in Alaska, Oregon, and Washington remained within 10 percent of their average during July and August before decreasing from September to December. Monthly average trips at the county level were variable, with values ranging between -50 percent and 50 percent, depending on the county, between May and October. Overall, Alaska experienced the largest reduction of trips to transit stations, whereas Idaho saw an increase in this type of trip. Data appeared to be missing from many of the PNW counties for this destination type (figure 4-1).

4.2. Changes in Public Transit Ridership in Major Cities

While not all destinations experienced reductions in trips, based on the Google mobility report, there was a consistently significant drop in ridership between April and September for all modes in the UZAs analyzed, as shown in figure 4-3. Ridership during January, February, and March was within 20 percent of normal ridership for all locations. However, in March, ridership dropped by 11 to 47 percent, and by May the reduction was as much as 40 to 95 percent. These results showed that ridership began to drop in March and became more significant in April and May. While ridership increased slightly over the following months of June, July, August, and September, they remained 11 to 92 percent lower than 2019 levels.

The most significant drops were in the cities of Bellingham, Olympia-Lacey, and Seattle in Washington. Boise, Idaho, and Wenatchee, Wash., experienced the least significant drops in ridership and appeared to be more resilient during the pandemic (figure 4-3). This trend was consistent across transportation modes. Our results also indicated that ridership for the bus mode reflected changes that were similar to the overall decline for UZAs in the Pacific Northwest. Boise, Idaho, had the smallest decrease in ridership, with values between 3 and 33 percent.

Ridership for the demand mode showed significant drops in ridership between March and September.

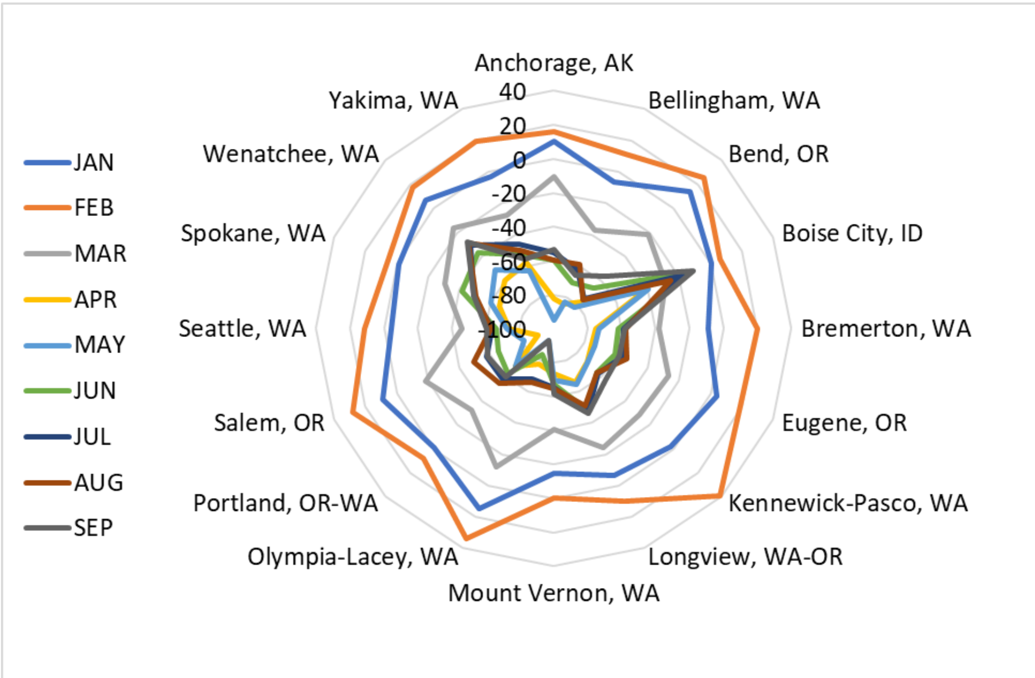

Figure 4-3 Ridership changes in comparison to the same month in 2019 for all modes

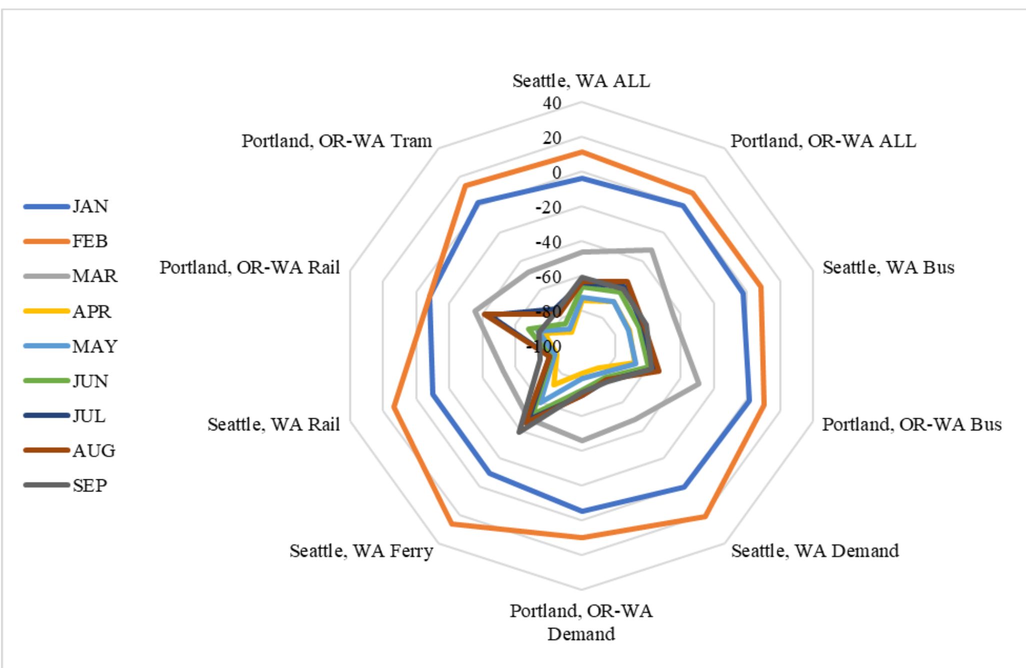

Figure 4-4 Ridership changes in Seattle and Portland in comparison to the same month in 2019, separated by mode

A more detailed description of ridership changes separated by mode share in Seattle, Wash., and Portland, Oregon, is presented in figure 4-4. This figure shows a new baseline for all transport modes for April through September 2020 in comparison to that of the previous year. Two transport modes, the rail system in Portland and the Ferry System in Seattle, experienced a less significant drop in ridership during July and August, with reductions of only 41 to 48 percent. This reduction was significantly less than that experienced by other modes within these cities in July (56 percent to 80 percent) and August (53 percent to 80 percent).

Changes to VRH and VRM for all modes are summarized in figure 4-5 and figure 4-6, which represent how the supply of public transit services changed over time during the pandemic. These services began to decline in March and experienced their greatest reductions during April and May. The largest service reductions occurred in Olympia-Lacey Wash.; Eugene, Oregon; Bellingham, Wash.; and Yakima, Wash. Services increased during August and September, particularly in Longview Wash.-Oregon; Portland, Oregon-Wash.; Wenatchee, Wash.; and Bend, Oregon. Anchorage, Alaska, temporarily reverted to pre-pandemic service levels during July. A summary of changes to vehicles operated in maximum service (VOMS) is presented in figure 4-7. The results showed that the peak number of vehicles decreased starting in March, in Bend, Oregon, and Yakima, Wash., followed by other areas in April. Anchorage, Alaska; Boise, Idaho; Olympia-Lacey, Wash.; Seattle, Wash.; and Spokane, Wash.; experienced the smallest decreases in VOMS values, whereas cities in Oregon such as Bend, Eugene, and Salem cut their services the most.

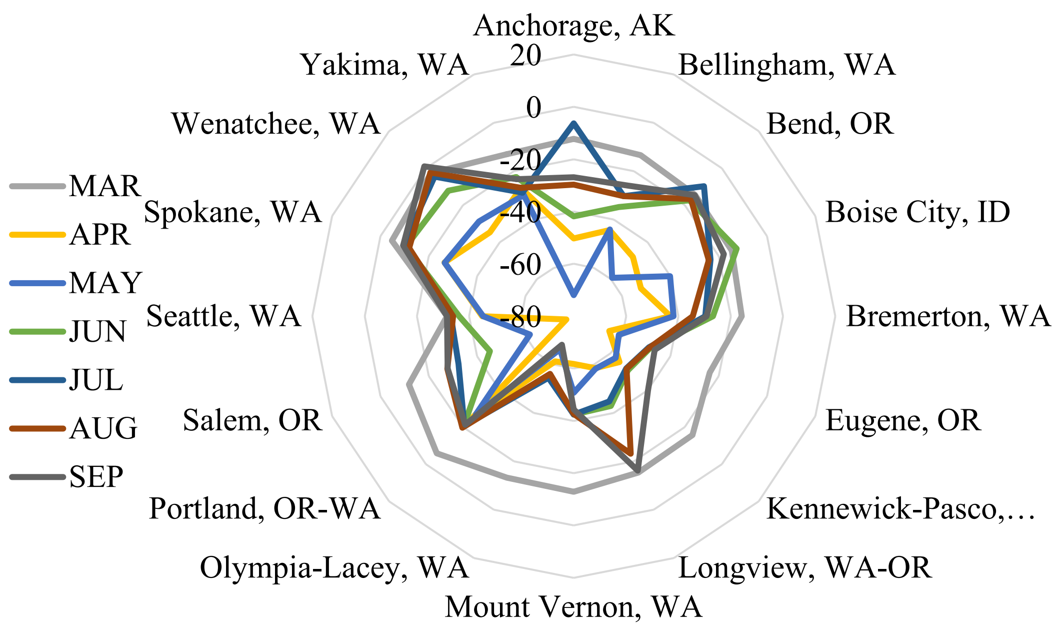

Figure 4-5 Changes in vehicle revenue miles (VRM)

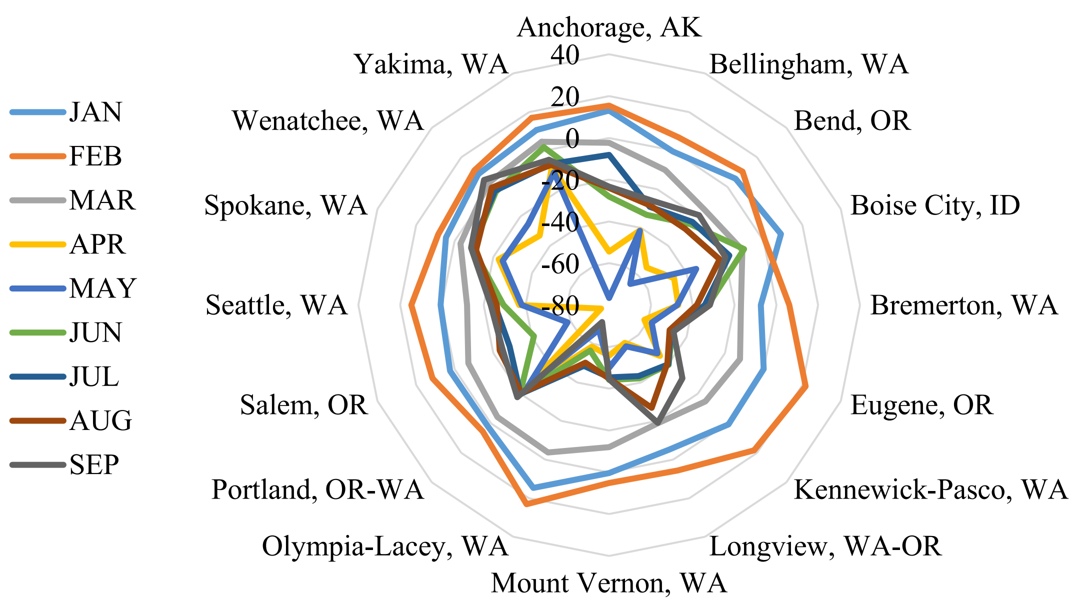

Figure 4-6 Changes in vehicle revenue hours (VRH)

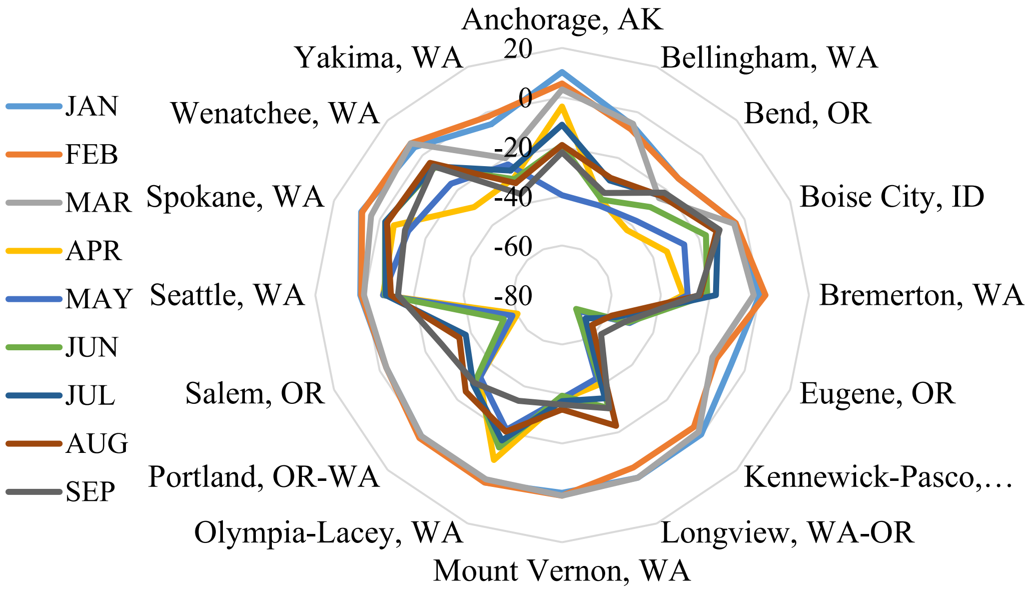

Figure 4-7 Changes in vehicles operated in maximum service (VOMS)

4.3. Results of the Regression Analysis

Results of the regression analysis are shown in table 4-1. Because the dependent variable for either reduction in trips to workplaces or the decline of ridership was negative, a negative coefficient means that as the value of an independent variable increased, there was a lower or more negative impact, i.e., a greater decrease. As shown in table 4-1, we found a significant positive relationship between transit ridership and infection rates. This result suggested that the rebound of ridership may have begun even though the spread of COVID-19 remained out of control. We expected sociodemographic variables to be significantly correlated with public transit ridership in major urbanized areas of the PNW region, but our results suggested otherwise. This finding was different from those of other studies focusing on the largest metropolitan areas such as Chicago and New York City (Hamidi & Hamidi, 2021; Hu & Chen, 2021a), where social vulnerability at the community level in these cities was found to be closely associated with ridership decline. However, our data included sociodemographic data and public transit statistics in different sizes of towns and cities; therefore, the effect may not have been evident and deserves more careful investigation.

Concerning the reductions of trips to workplaces, the findings were largely in line with the literature: counties in which more people were uninsured were more likely to exhibit smaller reductions in trips to workplaces. Similarly, counties with higher social vulnerability scores were also associated with smaller reductions in commuting trips, which implies that when the economy recovers, disadvantaged groups in the PNW may have to return to their workplaces for jobs that cannot be done from home (Lou et al., 2020). However, unlike other studies, we found that the African American population in the PNW region was surprisingly associated with a higher reduction in workplace trips, and tribal areas also exhibited higher reductions in work-related trips. Therefore, we contend that people in PNW tribal areas and other areas characterized by more racial diversity may remain at home during the pandemic, which may be associated with various programs that support minorities at the local level. We also found that more populated counties were associated with more evident reductions in workplace trips, partly because of more adherence to social distancing in urban areas. Furthermore, the average household size was a strong predictor of reductions in workplace trips, partly because of the need for parents to remain home to take care of children (Hamidi et al., 2020; Hamidi & Hamidi, 2021).

Table 4-1 Results of panel regression random-effect model

VARIABLES	(1) Reductions in trips to workplaces	(2) Decreases of ridership
Intercept	-11.047	-9.302
	(5.736)	(69.340)
% people without insurance	72.048***	72.507
	(19.933)	(156.013)
CDC social vulnerability scores	8.515***	16.740*
	(2.019)	(10.004)
Ln of total population	-1.219***	-0.004

	(0.369)	(2.863)
Average household size	-4.520**	-27.083
	(2.019)	(28.41)
% of American/Alaska native	-19.718***	-310.048*
	(5.253)	(186.091)
% of Hispanic	-10.285*	-40.445
	(5.455)	(27.500)
% of Non-Hispanic Black	-136.109***	-62.668
	(49.832)	(160.475)
Accumulative COVID19 cases per 1k pop	0.005	0.417***
	(0.020)	(0.114)
Stay-at-home: Months since the first shelter-in-place order insurance	0.664***	-1.101*
	(0.073)	(0.592)
N of observations	1085	112
R^2	0.324	0.271

Standard errors in parenthesis, ***p <0.01, ** p< 0.05, * p < 0.1

4.4. GIS Dashboard Development

In addition to analyzing data on mobility and ridership amid the pandemic, one additional effort of the project was the development of a dashboard and web mapping (see Appendix A for more details). Specifically, as shown in figure 4-8, our dashboard was one of the first to track the COVID19 outbreak at the regional level. Most data layers were made available by other developers. The Center for Systems Science and Engineering (CSSE) at John Hopkins University became the primary source for this information, which can be directly retrieved from its Github page (CSSEGISandData, 2020/2021).

With the dashboard, COVID-19 data can be tracked in near real-time (Dong et al., 2020a). For example, at the time of this writing (i.e., May 6, 2021), there had been just over 850,000 cases in the states of Washington, Idaho, Oregon, and Alaska and over 10,000 deaths. The hotspots of the outbreak in the region included King County (1,524 deaths), Pierce County (655 deaths), and Spokane County (629 deaths).

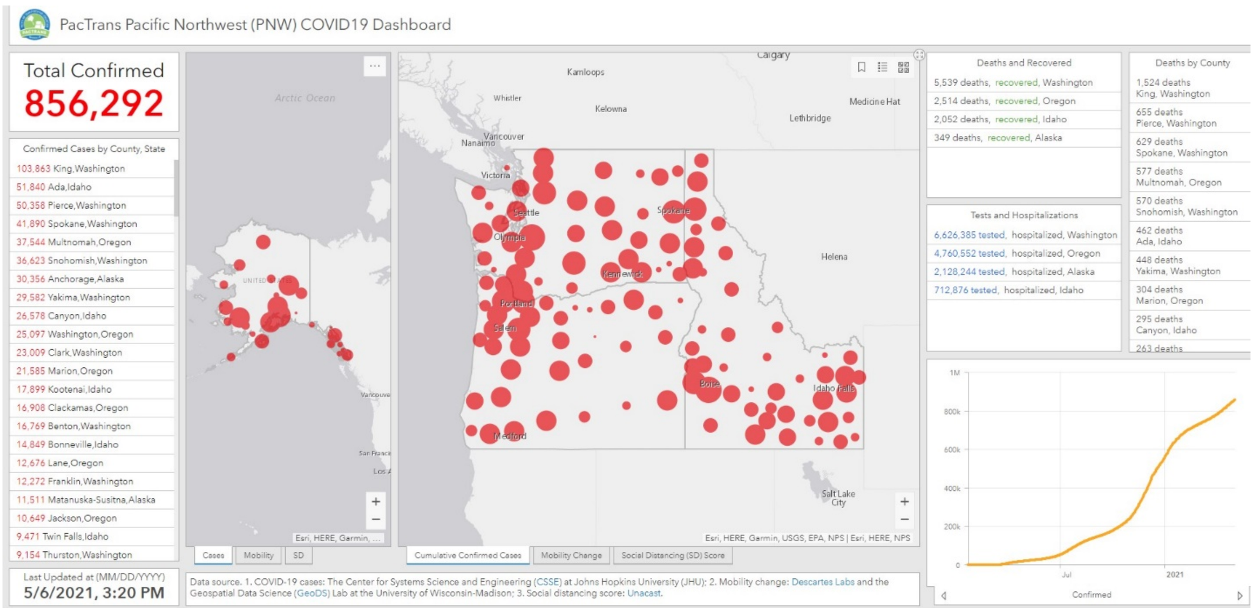

Figure 4-8 Dashboard and cases of COVID-19 in the PNW region

CHAPTER 5. Conclusions

The literature on changes in human mobility during the COVID-19 pandemic has been a burgeoning. However, relatively little is known about how this unprecedented public health crisis has affected travel behavior and public transit at the regional level. In this study, we utilized travel pattern data, obtained from Google and governmental data sources (i.e., FTA) to better understand the effects of the pandemic on travel behavior and transit ridership in the PNW region. A random-effect panel regression modeling approach was used to examine the sociodemographic dynamics of human mobility in general and ridership in particular amid the COVID-19 pandemic. We reached the following conclusions.

First, public transportation sectors were hard hit, and the recovery of ridership remains very slow in comparison to other modes of mobility. In contrast, trips to non-work destinations (e.g., grocery stores and parks) began recovering as early as the summer of 2020. Second, the effects of stay-at-home orders were evident at the beginning of the pandemic, while their impacts began to fade after reopening of the economy. We also found that sociodemographic characteristics played a vital role in shaping the landscape of human mobility in the second phase of the pandemic. As evidenced by our modeling results, vulnerable or disadvantaged populations may have disproportionately borne adverse impacts during this difficult time.

Finally, our study suggested that in the post-pandemic year of 2021, policymakers should continue to strategically align investments in the transportation sector and other infrastructure systems to address the inequality gap in society, which may have widened during the pandemic. Specifically, because public transit is a primary travel means for low-income and socially vulnerable groups, continued investment in public transportation should become a key objective in social and transportation planning, in conjunction with other objectives such as economic development, public health, and environmental sustainability. Last but not the least, some interesting topic—such as the potential of remote working, as demonstrated during the pandemic, and its impacts on alleviating traffic congestion and job-housing imbalance—deserve more attention in future studies.

CHAPTER 6. References

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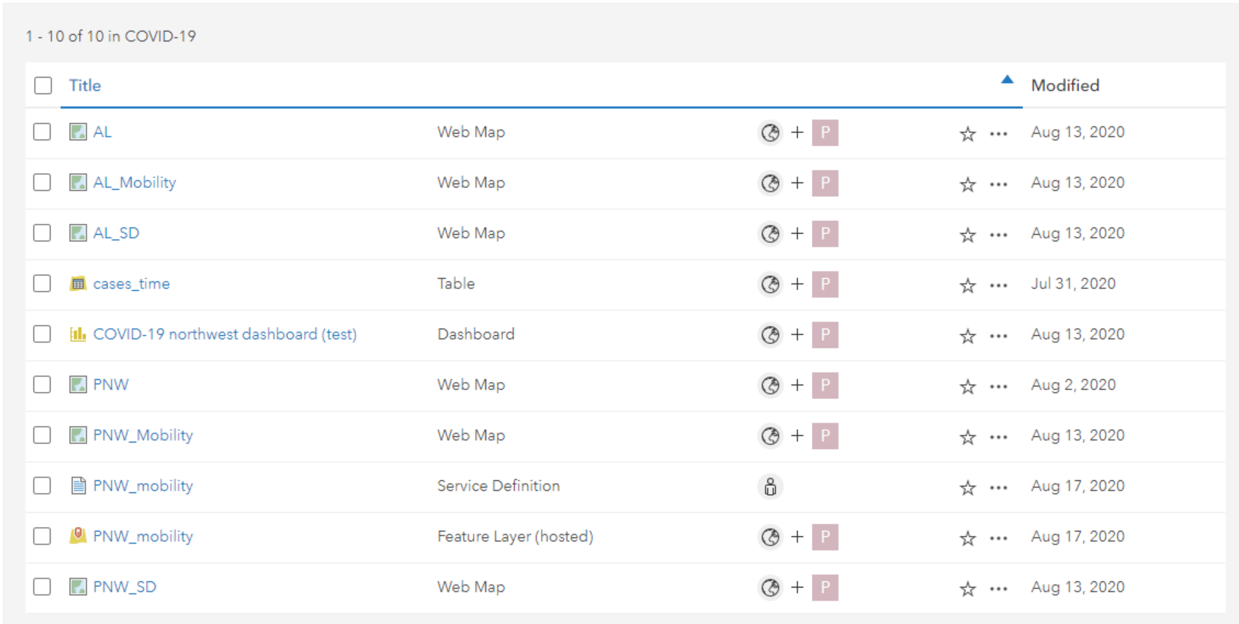
Appendix A: Steps to Develop the PNW COVID-19 Dashboard

The map element is the core component in the creation of a dashboard using the ArcGIS dashboard functions (https://doc.arcgis.com/en/dashboards/get-started/map-element-and-tools.htm). In the PNW COVID-19 dashboard, six maps were created, each one for a different purpose. They included confirmed cases (AL and PNW), mobility changes (AL_Mobility and PNW_Mobility), and social distancing (S.D.) score (AL_SD and PNW_SD) (see table A-1).

Table A-1 Indicators and sources of the PNW COVID-19 dashboard.

Indicator	Source
Confirmed case, County Level Deaths, County Level Deaths and Recovered, State Level Tests and Hospitalizations, State Level	JHU CSSE, https://systems.jhu.edu/; https://gisanddata.maps.arcgis.com/apps/opsdashboard/index.html#/bda7594740fd40299423467b48e9ecf6; https://uidaho.maps.arcgis.com/home/item.html?id=628578697fb24d8ea4c32fa0c5ae1843; https://uidaho.maps.arcgis.com/home/item.html?id=1cb306b5331945548745a5ccd290188e
Mobility change, County Level	Descartes Labs, GeoDS Lab@ UW-Madison, https://www.descarteslabs.com/; https://github.com/descarteslabs/DL-COVID-19; https://geods.geography.wisc.edu/covid19/physical-distancing/
Social Distancing Score, County Level	Unacast, https://www.unacast.com/; https://uidaho.maps.arcgis.com/home/item.html?id=ab72fb3e9bf24d9594f0b942718bffeb

a. In the maps regarding confirmed cases (PNW and AL), the core layers include the ArcGIS Living Atlas layer from the JHU CSSE and others (figure A-1). After opeingn the PNW or AL map with Map Viewer (the original web map tool with more functions) or with Map Viewer Beta (a user-friendly web map tool but with fewer functions; sometimes using both is needed), users can modify and maintain the map (for more details and useful functionalities, see https://doc.arcgis.com/en/arcgis-online/create-maps/create-maps-and-apps.htm).



1 - 10 of 10 in COVID-19

Title		Modified
AL	Web Map	Aug 13, 2020
AL_Mobility	Web Map	Aug 13, 2020
AL_SD	Web Map	Aug 13, 2020
cases_time	Table	Jul 31, 2020
COVID-19 northwest dashboard (test)	Dashboard	Aug 13, 2020
PNW	Web Map	Aug 2, 2020
PNW_Mobility	Web Map	Aug 13, 2020
PNW_mobility	Service Definition	Aug 17, 2020
PNW_mobility	Feature Layer (hosted)	Aug 17, 2020
PNW_SD	Web Map	Aug 13, 2020

Figure A-1 Current content in the PNW COVID-19 dashboard project

b. The COVID-19 Cases U.S. layer in the map, shown in figure A-2, is the core layer from the JHU. It is added by clicking on "Add layer," selecting Living Atlas in the drop-down list, and searching and adding "COVID-19 Cases the U.S." After adding the layer, users click on and modify it from the options in the right panel, which include the following:

   1) Filter the data from the four states (Idaho, Wash., Oregon, Alaska) by "Filter" and fill in the condition expressions.
   2) Change the symbol by selecting "Styles."
   3) Configure the pop-up message showing when others click on data points on the dashboard by selecting "Configure pop-ups."
   4) Other configurations like "Configure attributes" and "Properties."
   5) For more details, see "Work with map layers" in https://doc.arcgis.com/en/arcgis-online/create-maps/create-maps-and-apps.htm.
   6) Other layers such as USA State (Generalized) and USA Counties (Generalized) are also added from the Living Atlas.
   7) The cases state layer is from another published map from the JHU. It is added by searching "Coronavirus COVID-19 Cases V2" in the Living Atlas. The Unacast

Social Distancing Score (Latest Available) is a published layer from Unacast shown in ______________.

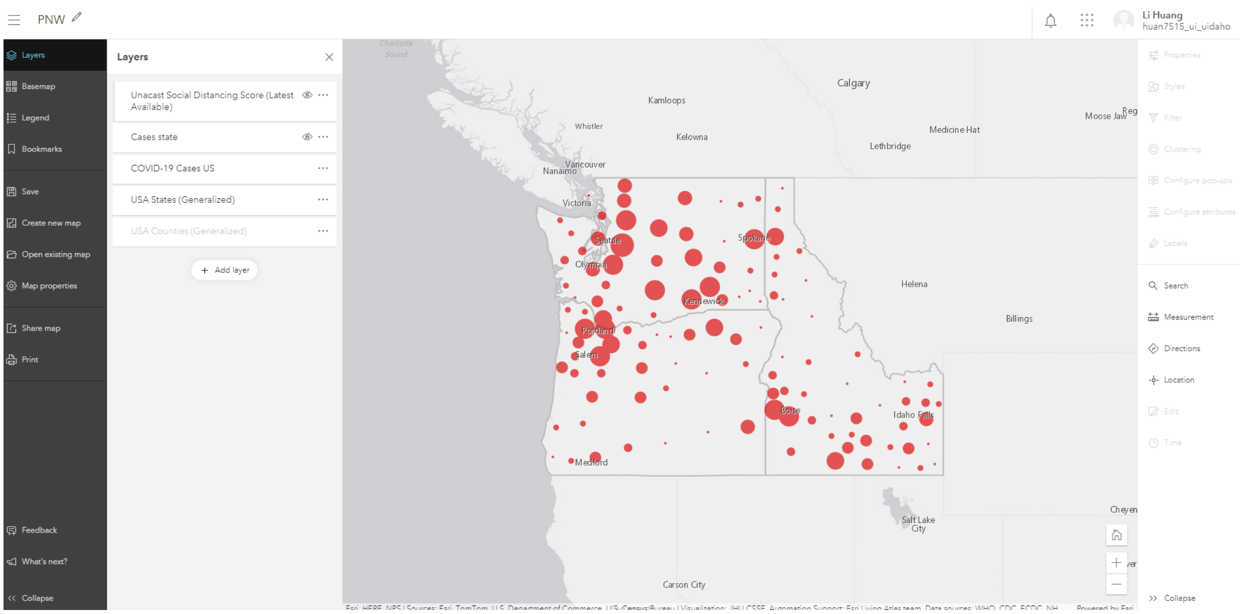


Figure A-2 Confirmed cases map.

c. The dashboard contains many other elements that can be extracted from the information on the map:

1) An indicator element shows the total cases. It uses the sum statistic from the field "Confirmed" in the "COVID-19 Cases U.S." layer in the PNW map.
2) A list element shows the confirmed cases by county and state. It is sorted by the field in (1) and uses syntax to display the number, the county name, and the state name.
3) An indicator element shows the last updated time of the JHU layer. It uses the trick to display only one row in the "COVID-19 Cases U.S." and the value in the "Last Update" field;
4) Two list elements show deaths and numbers recovered and the state's tests and hospitalizations. It uses the hidden layer "Cases state" in the PNW map.
5) A list element shows deaths by county.
6) The serial chart elements show Confirmed, Confirmed by State, Daily Cases by State, and S.D. Score by State information. They use the hidden layers "Cases state" and "Unacast Social Distancing Score (Latest Available)" in the PNW map.

7) A header panel element shows the title.

8) A rich text element shows the data source information.

9) For more details, see "Configure an element" and "Dashboard elements" in https://doc.arcgis.com/en/dashboards/get-started/create-a-dashboard.htm.

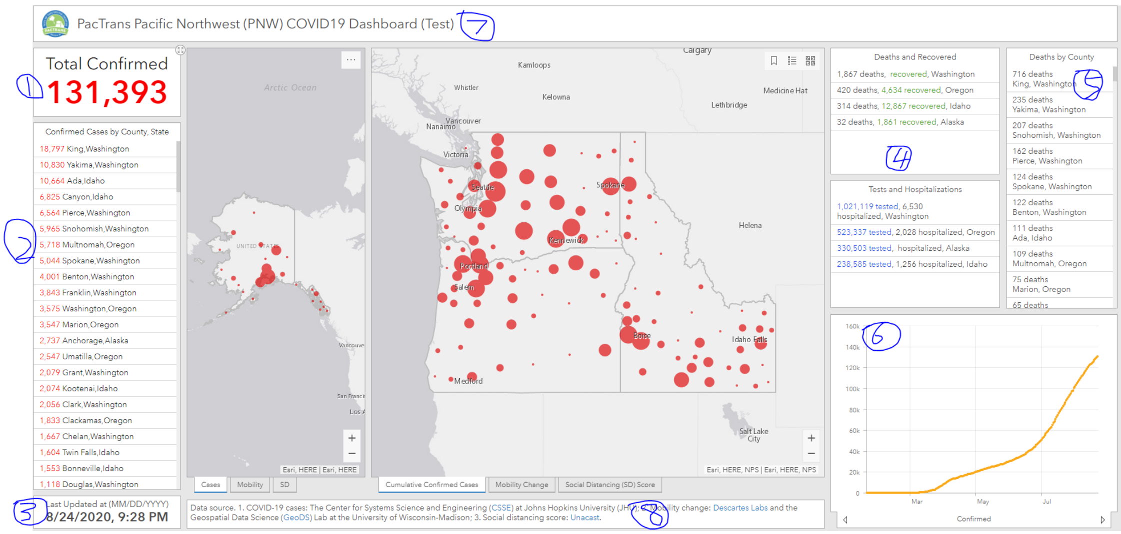


Figure A-3 Content displayed on the dashboard

d. The AL-related maps are copies of PNW-related maps but further filter the data for Alaska.

e. The making and maintaining of the Social Distancing Score maps (AL_SD and PNW_SD) are very much like those for the Confirmed maps (A.L. and PNW) but switch the core layer to Unacast Social Distancing Score (Latest Available).

f. For the topics of confirmed cases and social distancing scores, the mapping and updating are very convenient through ArcGIS online and the ArcGIS Living Atlas because the core layers are maintained and updated by the JHU and Unacast. But for the topic of mobility change, the Descartes Labs, GeoDS Lab@ UW-Madison, is not currently publishing the core layer in the Living Atlas but only through the CSV in Github. An ArcPro project and custom tool were created to solve this problem, as discussed in the following section.

g. Link spreadsheets to the GIS Dashboard by doing the following:

   1) Open COVID_GIS.aprx in ArcGIS Pro.

   2) Run the self-designed "Preprocessing daterow" tool in Toolboxes → COVID_GIS.tbx, fill in the path to the latest DL-us-mobility-daterow.csv, modify the SQL to select the date, and configure the output (figure A-4). This tool will filter the

daterow csv to the selected date and append the information to the County_daterow layer, which will be published. For more details, see how the tool is designed in model builder.

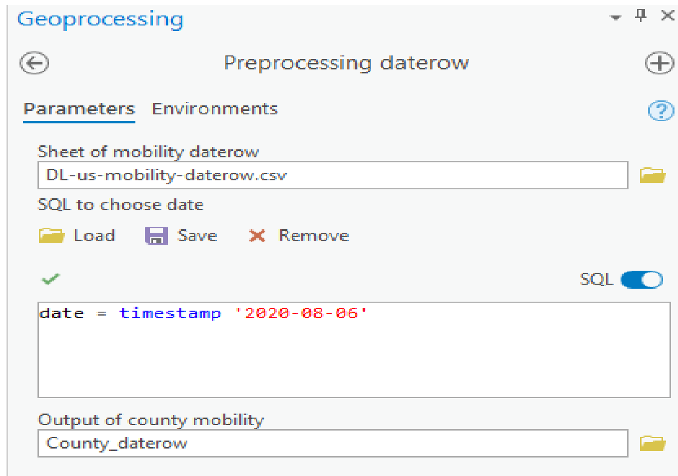


Figure A-4 Configuration of the custom tool

3) The map updates with county mobility. Ignore the warning 002858 after the tool has been run.
4) Click on the menu "Share→Web Layer→Overwrite Web Layer." Select PNW_mobility in the ArcGIS Online folder; it is the layer to be updated.
5) Click OK in the warning window. In Settings, select "Use the item description from the web layer." Type in the Summary and the Tags with "COVID-19." Select "Share with" Everyone, University of Idaho, and Pacific Northwest COVID-19 in Groups. Click on Publish and wait until it is done.
6) Steps 1-4 will update the web layer "PNW_mobility" in the ArcGIS online folder (figure A-1). This layer is used in the Web Map "PNW_Mobility" and "AL_Mobility". Because the layer is updated, the web map and dashboard are updated correspondingly.
7) Close and save the ArcGIS Pro project. Use what has been described from Part I to modify the map and layer settings in "PNW_Mobility" and "AL_Mobility."

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Appendix B: List of Public Agencies by Urbanized Areas in the PNW Region

Table B-1 Public transit agencies and FTA modes by urbanized area

Urbanized Areas	Agency	D.R.	V.P.	C.B.	C.R.	M.B.	R.B.	T.B.	A.R.	L.R.	S.R.	MG	YR	FB	T.R.
Anchorage, AK	Alaska Railroad Corporation								X						
	Municipality of Anchorage	X	X			X									
Bellingham, WA	Whatcom Transportation Authority	X	X			X									
Bend, OR	Central Oregon Intergovernmental Council	X		X		X									
Boise City, ID	Ada County Highway District		X												
	Valley Regional Transit	X				X									
Bremerton, WA	Kitsap Transit	X	X			X								X	
Eugene, OR	Lane Transit District	X	X			X	X								
Kennewick-Pasco, WA	Ben Franklin Transit	X	X			X									
Longview, WA-OR	River Cities Transit	X				X									
Mount Vernon, WA	Skagit Transit	X	X	X		X									
Olympia-Lacey, WA	Intercity Transit	X	X	X		X									
Portland, OR-WA	City of Portland										X				X
	City of Wilsonville	X				X									
	Clark County Public Transportation Benefit Area Authority	X	X			X									
	Ride Connection, Inc.	X				X									
	Tri-County Metropolitan Transportation District of Oregon	X				X				X			X		
Salem, OR	Salem Area Mass Transit District	X	X			X									
Seattle, WA	Central Puget Sound Regional Transit Authority			X	X					X	X				
	City of Everett	X				X									
	City of Seattle											X			
	County of Pierce													X	
	King County Department of Metro Transit	X	X			X		X			X			X	
	Pierce County Transportation Benefit Area Authority	X	X			X									
	Snohomish County Public Transportation Benefit Area Corporation	X	X	X		X									

	Washington State Ferries					X
Spokane, WA	Spokane Transit Authority	X	X		X	
Wenatchee, WA	Link Transit	X			X	
Yakima, WA	City of Yakima	X	X	X	X	

Notes: D.R.=demand response; M.B.= Motorbus; H.R.=Heavy Rail; L.R.=Light Rail; V.P.=Vanpool; C.B.= Commuter Bus; C.R.= Commuter Rail; R.B.= Bus Rapid Transit; T.B.= Trolleybuses; A.R.= Alaska Railroad; S.R.= Streetcar Rail; M.G.= Monorail and Automated Guideway modes; Y.R.= Hybrid Rail; F.B.= Ferryboats; T.R.= Aerial Tramways