Changes in When and Where People are Spending Time in Response to COVID-19

Nicholas Reinicke, Brennan Borlaug, and Matt Moniot

National Renewable Energy Laboratory

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Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

List of Acronyms

FIPS	Federal Information Processing Standards
LEHD	local employer–household dynamics
LODES	LEHD Origin–Destination Employment Statistics
MKDE	multivariate kernel density estimation
MSA	metropolitan statistical area
NAICS	North American Industry Classification System
NREL	National Renewable Energy Laboratory

Executive Summary

The COVID-19 pandemic has resulted in a significant change in driving behavior as people respond to the new environment. However, existing methods for analyzing driver behavior such as travel surveys and travel demand models are not suited for incorporating abrupt environmental disruptions. To address this, we analyze a set of high-resolution trip data and introduce two new metrics for quantifying driving behavioral shifts as a function of time, allowing us to compare the time periods before and after pandemic began. We apply these metrics to the Denver, Colorado metropolitan statistical area (MSA) to demonstrate the utility of the metrics. Then, we present a case study for comparing two distinct MSAs, Louisville, Kentucky; and Des Moines, Iowa which exhibit significant differences in the makeup of their labor markets. The results indicate that although the regions of study exhibit certain unique driving behavioral shifts, emerging trends can be seen when comparing between seemingly distinct regions. For instance, travelers in all three MSAs are generally shown to have spent more time at residential locations and less time in workplaces in the time period after the pandemic started. In addition, workplaces that may be incompatible with remote working, such as hospitals and certain retail locations, generally retained much of their pre-pandemic travel activity.

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1 Research Introduction

The COVID-19 outbreak and corresponding responses have reshaped the daily lives of many Americans. Attempts to limit the spread of the virus have motivated significant shares of the workforce to telework [1], brought about large increases in unemployment [2], and adjusted business operating strategies [3]. Combined, these trends contributed to stark reductions in absolute travel frequency throughout the height of social distancing in April 2020 [4]. However, empirical analyses of travel patterns indicate that, although absolute travel volume remained below pre-pandemic levels as of June of 2020, upward trends in travel frequency have been observed [5]. This upward tick in mobility occurred alongside novel travel behavior; whereas absolute trip counts have been recovering, emerging travel patterns appear dissimilar to pre-pandemic behaviors with defined morning and evening commuting peaks [6,7]. Observed upward trends in mobility—despite an absence of commuting trips—are consistent with prior teleworking research, which finds that commuting trips are replaced by other trips when given the opportunity to telework [8,9]. These emerging trends motivated a detailed analysis of a high-resolution transportation data set provided by INRIX to understand how driving behavior has changed since the onset of the pandemic.

The wide array of existing travel data sources and typical analysis techniques were found to be unsuitable for understanding the immediate changes in traveler behavior emerging in response to the pandemic. Historically, travel patterns are stable and predictable, leading to the generation of periodic travel surveys at the regional and national levels [10,11]. Data from travel surveys are used to calibrate more comprehensive travel demand models that characterize the movements of large populations at the regional level for informing questions about such topics as congestion mitigation [12]. Although these travel demand models do feature complex trip generation dynamics [13,14], they are often intended to characterize representative traveler behavior and are not informative for understanding responses to significant disruptions. More recently, large quantities of GPS data describing travel behavior have become ubiquitous primarily because of the proliferation of smartphones [15,16]. However, these same commercial GPS data sets are often aggregated to the infrastructure level (such as travel counts by corridor) and are typically targeted toward cities and municipalities interested in targeted transportation-system investments [17,18]. The large sampling rate throughout time and space afforded by GPS data sets are thus identified as valuable sources for understanding behavior change, although new techniques are required given the novel use case being pursued.

This analysis introduces new metrics for measuring changes in population-level driving behavior over time and space. Combined, these metrics suggest changes in where and when people are spending time. We apply these metrics using over 178 million light-duty-vehicle trips across three metropolitan statistical areas (MSAs) in the United States from January 2020 through June 2020, sourced from INRIX, a commercial automotive data provider. The highly resolved nature of the INRIX trip data, describing movements from close to 10% of the total vehicle population, facilitates empirical insight into how traveler behavior is changing with respect to specific location types such as residences, hospitals, and retail areas. Several findings emerge when analyzing behavioral trends in combination with location types. For instance, individuals are shown to spend more time at residential locations and less time in workplaces with a high probability of telework-capable jobs. On the other hand, workplaces incompatible with remote working, such as hospitals and certain retail locations, retain much of their pre-pandemic travel activity. Further, use of these metrics enables comparison of population responses across geographies with different workforce characteristics. We present findings for Denver, Colorado, an MSA familiar to the authors and used for calibration, in addition to a case study comparison between Louisville, Kentucky, and Des Moines, Iowa, two similar-sized MSAs with vastly different labor market characteristics and assumed teleworking opportunities.

The metrics described in this paper are applied to travel data before and after the COVID-19 outbreak to understand how travel behavior has changed. To simplify the discussion, these time periods are referred to as "pre-pandemic" and "during-pandemic" throughout the report. March 23, 2020, coincides with the implementation of many COVID-19 related responses in the United States and is used to demarcate pre- and during-pandemic categories [19,20]. Concretely, daily traveler behavior was averaged over all hours from January 1st, 2020 to March 23rd 2020 for the pre-pandemic time period and from March 24th, 2020 to June 30th 2020 for the during-pandemic time period.

2 Data Sets and Processing

2.1 INRIX Travel Data

The primary data set used for this analysis, which we procured from INRIX, contains approximately 14 billion driving trips for the entire continental United States. The data set captures trips that occurred between January 1, 2020, and June 30, 2020, making it an ideal candidate for observing driving behavior shifts that occurred after the onset of the pandemic in the United States. Although the data set contains trips for several vehicle classes, this analysis focuses solely on light-duty vehicles.

We aggregated trips contained in the INRIX data set to the census-block-group level, enabling simpler comparison to local contextual factors (such as land use). The final result of this aggregation was an origin–destination matrix that included a count of trips that occurred between census-block-group pairs by hour of day. We performed further aggregations at the MSA level using a spatial join between census block groups and the geographical boundaries of individual MSAs.

2.2 Local Employer–Household Dynamics (LEHD) Data

Aggregating INRIX trips to the census-block-group level enabled comparisons to local contextual information suggestive of trip purpose (e.g., education, hospital locations). We identified local employer–household dynamics (LEHD) information as an appropriate data set for providing labor market insights at the census-block-group level. Since 2002, the United States Census Bureau has released LEHD data products on an annual basis for the research and characterization of regional workforce dynamics across the country. These data are derived from a combination of sources, including administrative records, census and survey data, state unemployment insurance reporting, and public earnings records. The LEHD Origin–Destination Employment Statistics (LODES) is one such data product, containing tabulated jobs by workplace and residential location and disaggregated job counts by specific job type, employer, and worker characteristics [21]. For this study, we use 2017 LODES workplace area characteristics data for job counts by primary North American Industry Classification System (NAICS) sector at the census-block level. NAICS is the standard used by U.S. federal statistical agencies for classifying businesses for the purpose of publishing statistical data related to the U.S. business economy [22]. NAICS sectors represented in the data set are listed in the Appendix.

Block-level statistics are aggregated to the block-group level to correspond with processed INRIX trip aggregates described in Section 2.1. Census block groups are then assigned to MSAs through a geospatial join. The processed data set used in this analysis contains a set of census block groups with corresponding LODES workplace area characteristics aggregates for various MSAs in the United States. In order to differentiate between primarily residential and commercial block groups within an MSA, we apply a simple conditional: if the number of jobs exceeds the number of residents within a block group, the area is classified as "commercial"; otherwise, it is classified as "residential." We performed an additional classification on "commercial" block groups to determine their primary industry type. If the number of jobs within a commercial block group in a particular NAICS sector (e.g., "Finance and Insurance") exceeds 40% of total jobs in the block group, it is classified by that sector. If more than one sector exceeds 40% of jobs in a commercial block group (e.g., 47% "Retail Trade" and 41% "Information"), the sector with the highest share of jobs is assigned ("Retail Trade" in this example). Finally, if no individual sector exceeds 40% of jobs, the block group is given a "Mixed Business" designation. The classification of block groups by industry type was challenging given their large footprint and the high variability of land use within them. However, we found that the 40% threshold consistently identified dominant industry types and was therefore suitable for our purposes.

3 Methods

3.1 Inflows, Outflows, and Dynamic Population

Early analysis of GPS data throughout the pandemic demonstrated that travel behavior is changing [8]. Although aggregated trip counts over time are valuable, such analyses abstract the reality that an urban area comprises many distinct locations, each with unique trip generation and contextual factors. This understanding motivated further exploration using INRIX travel data to understand what locations may be associated with increases and decreases in trip counts by time of day. Location-based analysis was favored over corridor analysis to glean insight into possible trip generation factors, such as increased visits to public parks where socially distanced recreation might be feasible.

For each census block group, we averaged the flows of incoming and outgoing trips for each hour of the day overall all weekdays in the time period of interest. We excluded weekends in this analysis in an attempt to isolate typical commuting behavior. The results of this preprocessing step are two hourly traces per block group, containing the average number of incoming trips and outgoing trips over a select time period. Figure 1(A) shows the average number of daily weekday arrivals to and departures from the census block group confining the National Renewable Energy Laboratory (NREL) campus; note that trends shown are consistent with typical pre-pandemic traveler behavior with well-defined morning and evening commuting peaks.

Next, by taking the difference between the inflow trace and the outflow trace and computing the cumulative sum over the difference, the result is a new trace that estimates the average number of net travelers residing in a census block during a 24-hour period (referred to as the "dynamic population"). Figure 1(B) illustrates the dynamic population of the NREL census block group during the pre-pandemic and during-pandemic periods. Inspection of these traces immediately reveals that, although the absolute number of commuters has severely reduced since the onset of the pandemic, the few individuals continuing to travel to the NREL census block on workdays are arriving and leaving at similar times. Note that the dynamic population does not return to zero at the end of the 24-hour period. This error will be discussed in Section 5.

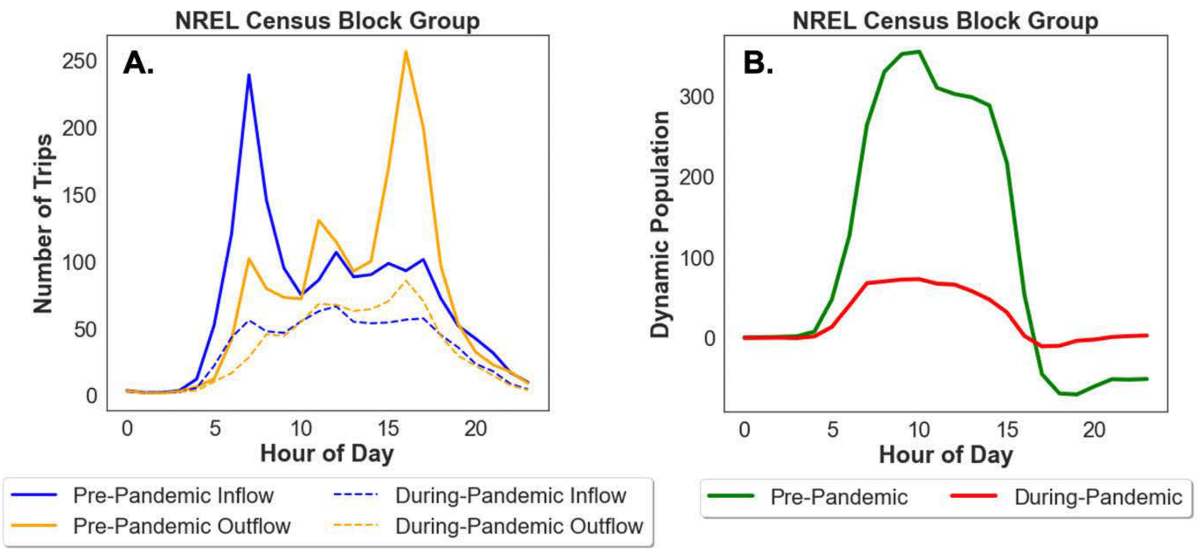

Figure 1. (A) Arrival and departure flows from the NREL census block group on weekdays before the COVID-19 outbreak. (B) Pre-pandemic and during-pandemic dynamic population curves associated with the NREL campus census block group.

3.2 Signal Analysis Metrics

Although the comparison for pre-pandemic and during-pandemic travel behavior at the block-group level is insightful, it becomes necessary to quantify the change mathematically such that multiple block groups can be aggregated in a meaningful way. Insights are broken out across two dimensions: changes in *where* travelers are spending time (associated with changes in the area under the dynamic population curve) and changes in *when* travelers are spending time (associated with changes in the shape of the dynamic population curve). These dimensions are illustrated conceptually in Figure 2 with blue and orange arrows, respectively.

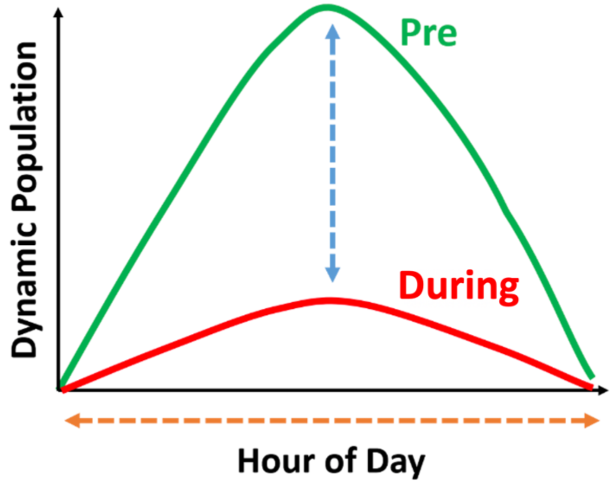

Figure 2. Conceptual representation of pre- and during-pandemic dynamic population curves for a fictitious census block group

In order to quantify the change in where travelers are spending time, we applied Equation 1 to the pre-pandemic and during-pandemic traces. The result of this equation is the relative change in vehicle hours at a location across the 24-hour period (referred to as "dynamic population shift"). Positive values suggest an increase in travelers spending time at a location, whereas negative hours suggest a reduction.

$$\frac{\int P_{during}(t) \; - \int P_{pre}(t)}{\left|\int P_{pre}(t)\right|} \tag{1}$$

We quantified the change in behavior across time by comparing the correlation (Pearson's correlation coefficient) between dynamic population traces pre- and during-pandemic. We used the resulting R^2 value to suggest how similar travel behavior was occurring throughout time. Note that traces with vastly different sizes might still be highly correlated; an R^2 value calculated using the traces in Figure 2 would produce a high correlation coefficient given the similar trace shapes.

3.3 Source or Sink

Given the nature of the dynamic population traces, it is possible to broadly classify a given block group as a "source" or "sink." Here, we define a source as a block group with a negative value for the size of the dynamic population over a 24-hour period. This indicates that vehicles are leaving the block group for extended periods throughout the day (e.g., commuting to work). We define a sink as a block group that has a positive value for the size of its dynamic population. This indicates that the block group is receiving travelers over a 24-hour period. Figure 3 shows an example of both a source (pre-pandemic) and a sink (during-pandemic) dynamic population trace for a census block group in the Denver MSA.

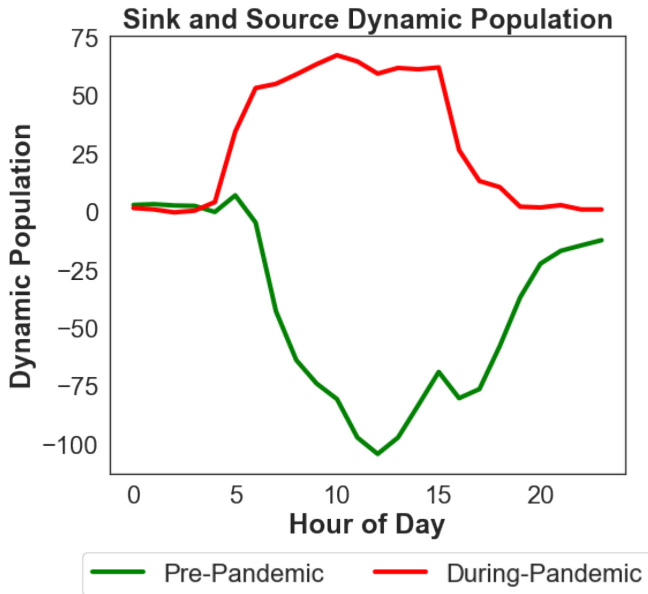

Figure 3. Example of a Denver block group that demonstrates behavior as both a sink (red) and a source (green)

Note that Figure 3 demonstrates that it is possible for a source to become a sink and vice versa. In this case, the dynamic population shift metric would capture the large swing in vehicle hours but would not explicitly indicate that this phenomenon has occurred. For reference, the dynamic population shift metric for this block group is 1.70 and the correlation is 0.53. This particular block group contains primarily residential and recreational spaces, including a state park. Figure 3 indicates that many more travelers are spending time in this block group during-pandemic relative to pre-pandemic. Although this could be a causal effect of the pandemic, it could also be induced by seasonal effects; generally, recreational spaces in the area see more use during the summer months relative to the winter months, which happens to coincide with the during- and pre-pandemic time periods, respectively.

3.4 MSA Selections

The signal analysis metrics introduced in Section 3.2, namely population shift and correlation, facilitated insight into traveler behavior change at a large scale. We analyzed all traveler flows aggregated to the census-block-group level within exemplar MSAs to demonstrate what findings emerge when pairing the processed INRIX travel data and NAICS contextual factors. We first explored the Denver MSA (Section 4.1), given the authors' familiarity with the region, and used it to calibrate the census-block-group categorization methods to confirm results were consistent with experiences.

Next, we identified two separate regions with very different labor markets and predicted telework-capable populations by combining multiple data sets published by the U.S. Bureau of Labor Statistics. We identified MSAs with vastly different predicted telework-capable populations to compare the ways in which commuting behavior has changed as a result of the pandemic. We calculated teleworking likelihood by MSA using two sources. The first data set synthesizes values from the 2017–2018 American Time Use Survey suggesting the probability that workers might be capable of teleworking by industry [23,24], and the second [25] describes the composition of labor markets by MSA as of late 2019. We identified Louisville, Kentucky, and Des Moines, Iowa, as two MSAs with similar labor market sizes but measurably different estimated teleworking capabilities (31.8% and 49.4%, respectively). Figure 5 compares the labor market of each of these MSAs by looking at total jobs per NAICS classification. Changes in traveler behavior across these two regions are compared in Section 4.2.

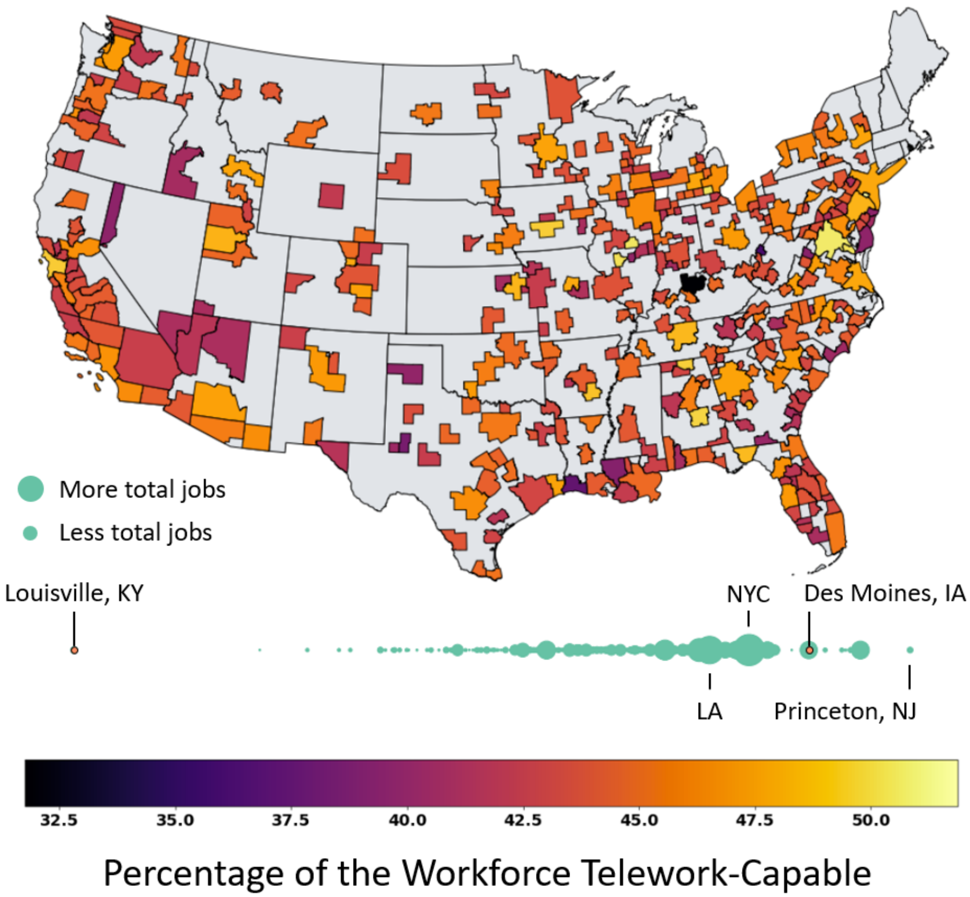

Figure 4. Estimated share of telework-capable jobs for labor markets in the contiguous United States

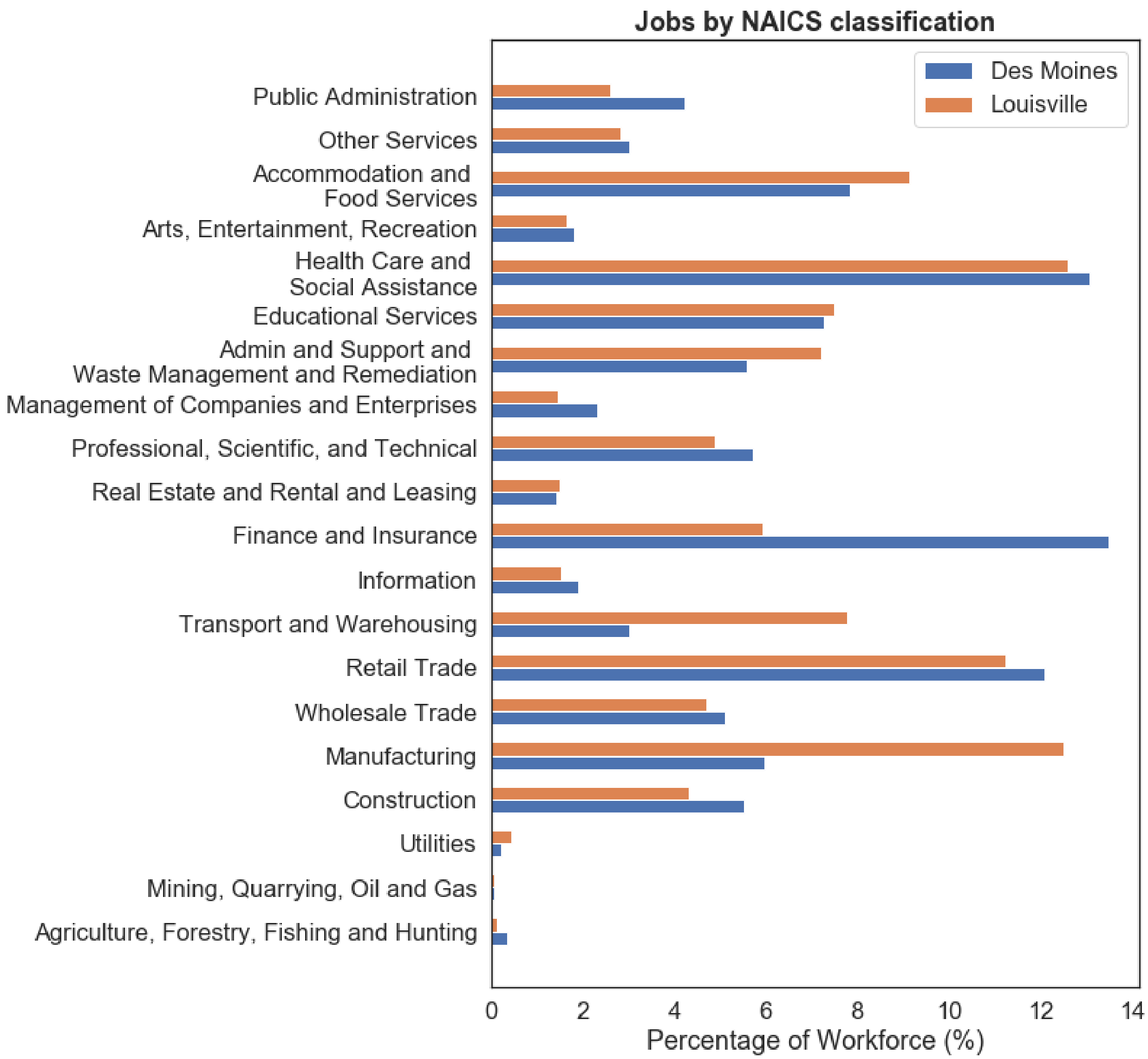

Figure 5. Job counts by NAICS classification in Des Moines and Louisville

4 Results and Discussion

4.1 Single MSA Analysis: Denver, Colorado

We applied the signal analysis metrics introduced in Section 3.2 to all 1,795 census block groups in the Denver MSA. Additionally, we integrated NAICS codes for each census block group using the LODES data set. Results for each census block group are shown in Figure 6, plotted as correlation on the y-axis against dynamic population shift on the x-axis. Scatter point size is used to indicate the total number of trips associated with each census block group, given that the two metrics calculated thus far are both relative parameters. Also included are the top-six census-block-group classification categories (note that all block groups have been classified but only some are shown for clarity).

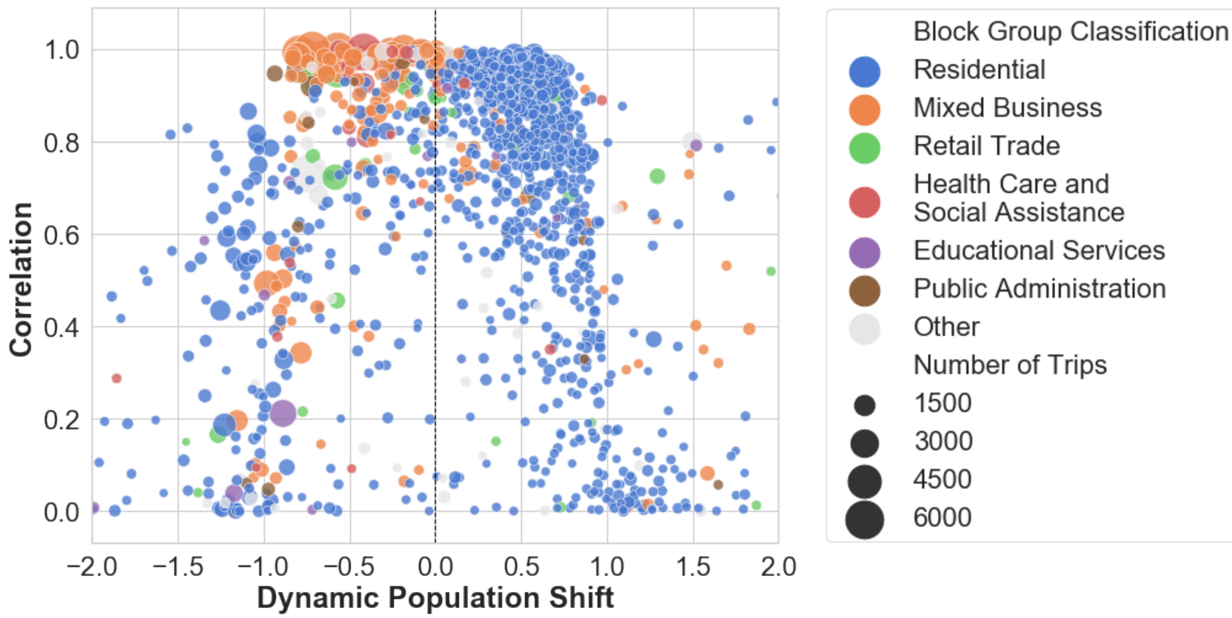

Figure 6. Mobility changes across two dimensions for the 1,795 census block groups in Denver, Colorado

Inspection of Figure 6 reveals several interesting trends. First, the overwhelming majority (90%) of census block groups with an increase in relative vehicle hours are residential areas. This finding is intuitive upon inspection; most residential areas served as significant population sources during the day pre-pandemic, whereas Figure 6 suggests that more people are staying at home during-pandemic. Another emerging trend is the high correlation between pre- and during-pandemic travel behavior throughout time of day (y-axis) for healthcare and retail locations, which have a trip-weighted average correlation of 0.92 and 0.78, respectively. These locations typically require the physical presence of employees and customers typically must travel there despite the presence of the pandemic (such as to obtain groceries or medical assistance). The healthcare and retail categories contrast with educational services, which exhibits a trip-weighted average correlation of 0.38, indicating a large shift in travel behavior across the day. Figure 7 provides two example block groups from the Denver MSA to illustrate the differences between a Retail block group and an Education block group. Although time spent at the retail census block group appears similar before and after the onset of the pandemic, the work-day behavior observed during-pandemic at the education census block group has significantly decreased and shifted to later in the day.

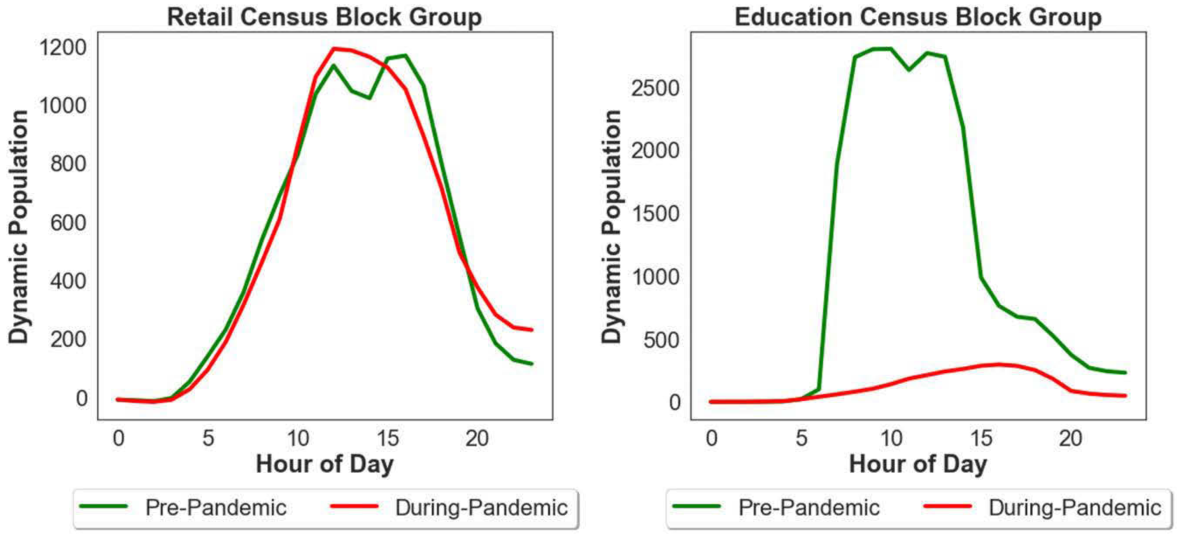

Figure 7. (Left) Dynamic population traces for a census block group categorized as Retail, showing similarities in traveler behavior before and after the pandemic outbreak. (Right) Dynamic population traces for a census block group categorized as Education, showing significant changes in traveler behavior after the pandemic outbreak.

4.2 Comparison Between Two MSAs: Louisville, Kentucky, and Des Moines, Iowa

Given the ability to aggregate these metrics for an entire MSA, the next step in this analysis was to compare two unique MSAs in order to observe differences in traveler behavior across geographies. As described previously, the two MSAs for comparison are Des Moines, Iowa, and Louisville, Kentucky. Rather than comparing the dynamic population shift and the correlation for all census blocks, we isolated select NAICS sector classifications. We selected these classifications by extracting the top-six overlapping categories between the two MSAs. Figure 8 and Figure 9 show a multivariate kernel density estimation (MKDE) for the select classifications in each MSA. Each MKDE is weighted by the number of trips that occurred in each block group during the week (Monday through Friday).

Comparing the two MSAs, it seems noteworthy that most of the classifications exhibit similar distributional shapes. This could suggest that travelers in each MSA are responding to the pandemic in similar ways regardless of the stark difference in labor markets. For example, it appears that both exhibit similar distributions in the Residential sector. Indeed, inspecting Table 1 and Table 2, we notice that the two metro areas share very similar statistics for both the aggregate dynamic population shift and correlation. Given the positive average dynamic population shift, this may suggest that the driving population in both metro areas is staying home more often relative to the pre-pandemic period.

A notable exception to these similarities between MSAs is the Retail Trade sector, which seems to vary significantly between Des Moines and Louisville. Inspecting Table 1, it appears that the driving population in Des Moines is spending relatively more time in these block groups, whereas the population in Louisville is spending relatively the same amount of time in these block groups. In addition, the variance for the Des Moines Retail Trade sector with respect to population shift is quite large relative to the same measure in Louisville.

Figure 8. MKDE plot for select NAICS classifications in Louisville, Kentucky

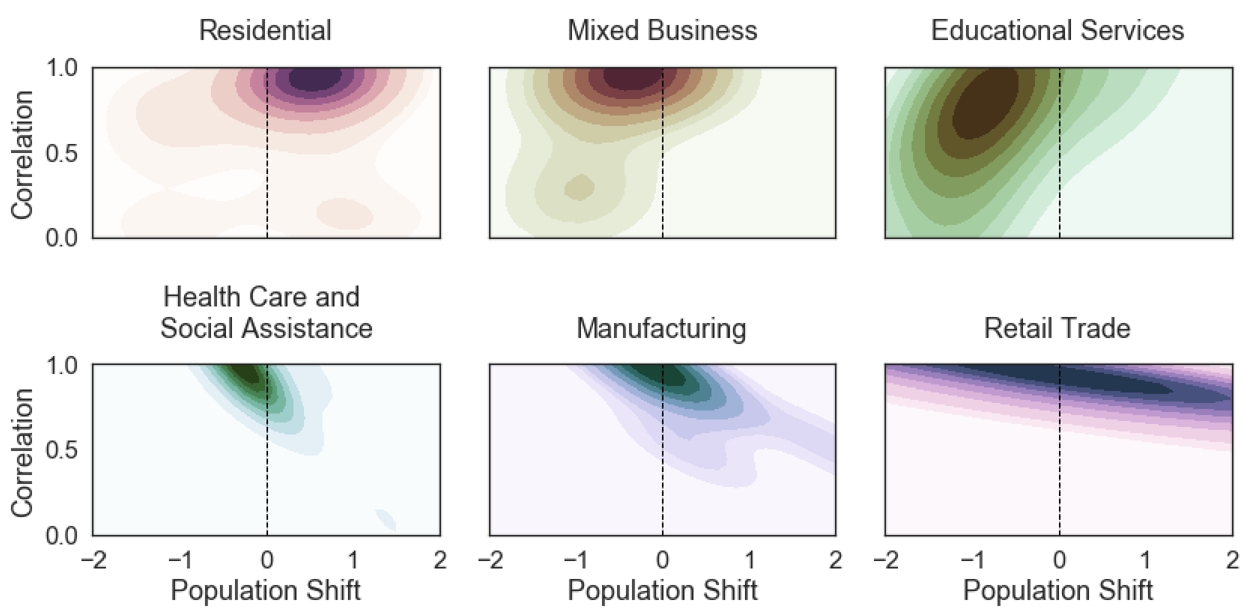

Figure 9. MKDE plot for select NAICS classifications in Des Moines, Iowa

Table 1. Dynamic Population Shift Statistics

Block Group Classification	MSA	Weighted Average	Weighted Variance
Residential	Des Moines	0.40	1.07
	Louisville	0.32	1.05
Mixed Business	Des Moines	−0.36	0.97
	Louisville	−0.39	0.57
Educational Services	Des Moines	−0.70	0.58
	Louisville	−0.76	0.41
Health Care and Social Assistance	Des Moines	−0.17	0.36
	Louisville	−0.42	0.23
Manufacturing	Des Moines	0.21	0.69
	Louisville	−0.13	0.68
Retail Trade	Des Moines	1.07	2.96
	Louisville	0.07	0.64

Table 2. Dynamic Population Correlation Statistics

Block Group Classification	MSA	Weighted Average	Weighted Variance
Residential	Des Moines	0.79	0.29
	Louisville	0.75	0.29
Mixed Business	Des Moines	0.81	0.29
	Louisville	0.84	0.23
Educational Services	Des Moines	0.69	0.31
	Louisville	0.67	0.29
Health Care and Social Assistance	Des Moines	0.93	0.20
	Louisville	0.98	0.06
Manufacturing	Des Moines	0.86	0.20
	Louisville	0.86	0.23
Retail Trade	Des Moines	0.83	0.24
	Louisville	0.78	0.24

Table 1 and Table 2 reinforce certain findings from the MKDE plots, such as the relative similarity between the two MSAs. For example, individuals in both MSAs are spending less time in Mixed Business locations and more time in Residential locations. In addition, time spent at locations tagged as Education Services has contracted significantly in both MSAs.

5 Limitations: Dynamic Population Trace Error

Due to the nature of certain devices that supply trip-level data to INRIX, some trip origins appear at a location other than where the trip definitively started. These devices may exhibit a delay when starting to record a trip and thereby misattribute the origin location. This data flaw appears throughout this analysis when computing the dynamic population traces. For example, imagine that 100 travelers enter a given block group during the morning and 25 of them possess devices that will delay reporting a trip start. Because the devices only exhibit said delay for trip starts, 100 unique trip destinations will be reported for the block group. However, when the 25 travelers with late-reporting devices leave the block group, the devices may fail to start recording until the travelers have already left the block group, thus misattributing the trip to a nearby location. What remains would be a dynamic population trace that begins at zero, rises up to 100 during the day, but only drops to 25 at the end of the day (rather than returning to zero). Figure 7 demonstrates this phenomenon quite clearly, as the dynamic population traces exhibit non-zero values at the end of the day. We refer to this error as "dynamic population error."

Given this potential explanation for this error, we would expect it to "cancel out" over the entire MSA presuming there were no trips that "leaked" across the boundary of the MSA. Figure 10 is a distribution of the dynamic population error for each block group in the Denver MSA during the pre-pandemic time period. Looking at the distribution, we do observe that the error exhibits a mean of approximately zero.

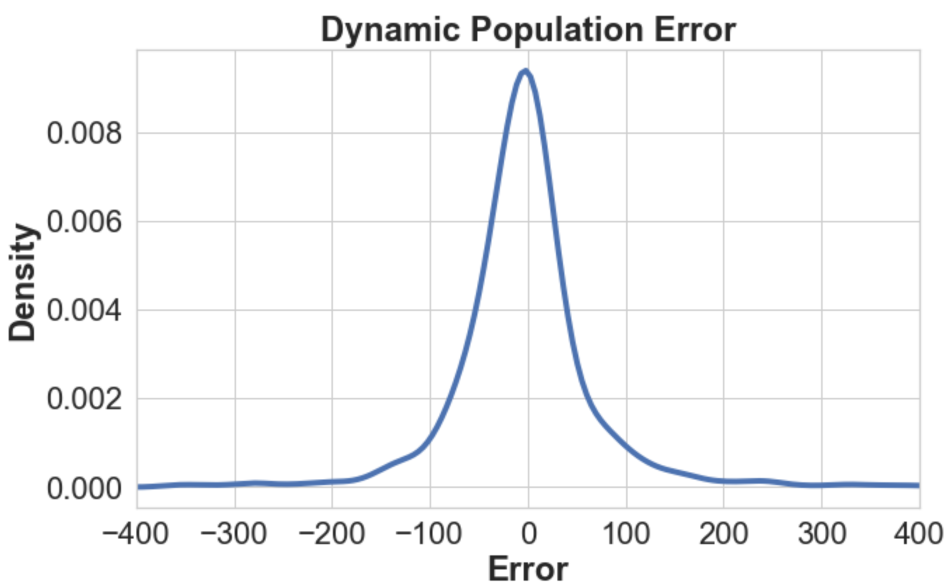

Figure 10. Dynamic population trace error distribution in Denver, Colorado

In a future analysis, it would be important to compare the dynamic population error over time at the block-group level to quantify how much noise it introduces into the dynamic population shift metric.

6 Conclusions and Future Work

The COVID-19 pandemic has resulted in a significant shift in driving behavior as people respond to the new environment. This report presents a set of new metrics for quantifying that shift in time and space. These metrics can be aggregated up to a higher level to analyze a larger geography or compare differences between multiple geographies. To illustrate this, we selected and analyzed three distinct MSAs. The results illustrate that although each region of study exhibits certain unique driving behavioral shifts, comparing between two seemingly distinct regions can reveal emerging trends. For example, when looking at a comparison between Des Moines, Iowa, and Louisville, Kentucky, the correlation and shift distributions are alike in both the Residential and Mixed Business block groups. This could suggest a similar behavioral change in both areas despite varying labor market compositions between the MSAs.

Although this analysis focuses squarely on the travel behavior effects after the onset of the COVID-19 pandemic, these metrics can certainly be applied in other contexts. For example, presuming access to sufficient data, these metrics could be applied to examine general mobility behavioral trends over multiple years for a given geography. Moreover, although we identify only three MSAs in this analysis, we intend to scale these metrics and apply them in a national context, indexing individual MSAs against national averages. Finally, there are opportunities to further explore relationships between behavior change and telework propensity by validating these metrics against other data sets that capture changes in driver behavior pre- and during-pandemic.

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Appendix: NAICS Codes

Table A-1. NAICS Sectors

NAICS Description	NAICS Sector
Agriculture, Forestry, Fishing, and Hunting	11
Mining, Quarrying, and Oil and Gas Extraction	21
Utilities	22
Construction	23
Manufacturing	31−33
Wholesale Trade	42
Retail Trade	44−45
Transportation and Warehousing	48−49
Information	51
Finance and Insurance	52
Real Estate and Rental and Leasing	53
Professional, Scientific, and Technical Services	54
Management of Companies and Enterprises	55
Administrative and Support and Waste Management and Remediation Services	56
Educational Services	61
Health Care and Social Assistance	62
Arts, Entertainment, and Recreation	71
Accommodation and Food Services	72
Other Services [Except Public Administration]	81
Public Administration	92