The Rise of the Remote Work Lifestyle and Its Impact to Travel

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DATASCI 200 Section 4, Spring 2024

Background

The COVID-19 pandemic impacted the daily lives of millions of people. Social distancing mandates implemented by various U.S. states resulted in most people staying at home. As restaurants, recreational facilities, offices, and schools transitioned to remote operations, people changed their travel behavior. A study conducted in May 2020, with 1203 participants, highlighted that during the pandemic, travel distances shortened, and the frequency of trips decreased. Furthermore, the study emphasized that during the COVID-19 pandemic, factors affecting travel decisions, like time, comfort, and cost under normal circumstances, became less important. Instead, concerns related to infection, such as wearing masks and social distancing, became more important than traditional factors. (Abdullah, 2020).

The pandemic not only altered travel behavior but also transformed the workforce environment. Another study, which surveyed 50,000 individuals online in April and May 2020, discovered that around half of employees who worked before the COVID-19 pandemic are now working from home. Among them, 35.2% mentioned shifting from commuting to remote work. This study also suggested that states with a higher concentration of information-related jobs, such as management, professional, and related occupations, were more likely to transition to remote work. Additionally, there was significant variation among states in the proportion of individuals switching to remote work compared to those still commuting (Brynjolfsson, 2020).

The significant rise in remote job opportunities, combined with the emergence of the COVID-19 pandemic, has greatly impacted people's lives, including their travel behavior both during and after the pandemic.

Problem Statement and Research Questions

This project aims to investigate the impact of the COVID-19 pandemic and the rise of the work-from-home (WFH) lifestyle on people's daily lives. Specifically, we seek to understand changes in travel behavior before, during, and after the pandemic using datasets measuring travel distances from home. Additionally, we aim to explore variations in WFH job opportunities across different states within the US and determine if these variations correlate with changes in travel habits. From this problem statement, we propose the following research questions that we seek to answer:

- How have people's tendency to travel changed with (1) the COVID-19 Pandemic and (2) the new work-from-home lifestyle?
  - Which states are more likely to have work-from-home job postings and travel? Does the number of postings in a given state have any impact on people's travel habits?
  - Did COVID-19 change the way we travel compared to the pre-pandemic era?

Data Sources

In order to answer the research questions above, we will be utilizing two data sources for this project: Trips by Distance (Titlow, 2020), and Work From Home (WFH) Map (Hansen, 2023).

Trips by Distance is a dataset produced by the Department of Transportation that compiles anonymous data from mobile phones throughout the nation to calculate the distance a given population traveled away from home. The data defines a "trip" as any movement away from home that lasts longer than 10 minutes. The columns are sectioned into buckets of trip distance ranging from less than one to greater than 500 miles, where the values under the column represents the number of people who traveled that distance in a given day (Appendix A.1). The data is tracked on a daily basis for the whole U.S., state, and county from January 1st, 2021 until March 3rd, 2024. The dataframe has a shape of (6007914 rows, 22 columns).

The Work from Home (WFH) Map will be the second datasource that we utilize and is a similar list of national, state, and county level dataset that tracks the percent of new remote job postings for each month (Appendix A.2). The data was captured from January 1st, 2019 until September 1st, 2024 and is captured on a monthly basis with a shape of (2907 rows, 10 columns).

For the purposes of this analysis, we will be looking solely at national and state level data and will not be reviewing the county level data. We are looking at these two levels in order to determine if the national data for WFH job postings and trips is representative of several key states. Exploring on a county level can be included as part of a future study.

Variables Used and Modified

In the Trips DataFrame, we will be utilizing the columns “Population Staying at Home” and “Population Not Staying at Home” to calculate a “Total Population” column, or the sum of these two variables. We can be confident that the sum of the “Total Population” column is representative of the state’s actual population if we compare the average population of California from our summed data (39.5 million people) and compare it to California's current population (39.03 million people), see Appendix A.4. for the total population calculation of all states.

Because some states have significantly more people living in them than others, we know that this will mean that the states with higher populations will have significantly more trips than those with smaller populations. Since the purpose of this study is to observe the behavior of travel and WFH on an individual basis, we do not want to only focus our results on the states with the highest population. As a result, we will be measuring our trips on a **per capita basis**, where we will divide each of the different trips columns by the total population of the state or nation. In this manner, we should be able to see how an individual citizen of the state travels on a regular basis over the course of the dataset’s timeframe.

Another note is that the trips dataset is collected on a daily basis while the WFH data is developed on a monthly basis. Because we would like to look at the relationship between the two, we need to convert the trips dataset to a monthly basis. In order to do so, we will be using the datetime module to convert the date into a “Month Year” column that will be a datetime object that converts the date from the trips dataset into the first day of the month for that year. We will then use the groupby() function to group by the “State Postal Code” column and the “Month Year” column. When we conduct the groupby() call, we will sum all the columns that record the number of trips, but we will need to take the average of the “Total Population” column, to keep the total population on the same order of magnitude.

As explained in the “Data Sources” section of this report, the trips data has data up until 3/2/2024. Because it only has data on the first two days of the month of March in 2024, we will remove the March 2024 “Month Year”, because that data will not show the full number of trips over the course of that month.

The WFH dataset, on the other hand, does not require any further manipulations and we will mainly be focusing on the “State Code”, “Month Year”, and “Percent” columns. Once we have gotten the trips dataset in the form explained above, we will then merge the two datasets into one on the “Month Year” and “State Code " columns. We have also acknowledged the fact that the trips data set has been collected for a longer period of time than the WFH dataset; however, to still observe all the data, we will be conducting a left merge (where the trips data is the left dataset and the WFH data is the right dataset). In this manner, we will have the full extent of both datasets in this new dataframe.

Finally, the above analysis will also be completed on the national level. For the trips dataset, this means we will filter the level only for the “National” level and for the WFH dataset, we will use the sheet_name = “country_by_month” and filter for the United States. Once we create the national level dataframe, we can repeat the same variable manipulations as above.

Methodology

Data Cleaning & Preparation

We began our analysis by exploring each dataset individually, to conduct sanity checks and clean the data accordingly. This process included the following steps:

- Examining the column structure and data types
- Standardizing column names by making lowercase, replacing spaces with underscores
- Splitting the Trips and WFH datasets into state level and national level subsets
- Assessing value counts for each column and evaluating presence of null values
- Aligning date column format and level of aggregation between the two datasets
- Removing columns not needed for analysis

During this initial phase, we observed that there were some null values in the Trips data for county level data, while the WFH dataset had zero nulls. This was expected, and did not impact our analysis as we omitted the county level Trips data.

A key part of our data cleaning process was manipulating the date columns. Since the Trips data was aggregated by day, while the WFH data was aggregated by month, we had to group the Trips dataset so that the two could be merged cleanly. Also, the WFH data had separate columns for year and month that needed to be combined into a single date column. Once these steps were complete, the datasets could be merged for analysis.

We also checked the date ranges for each dataset, and found that the Trips data ranged from January 2019 to March 2024, while the WFH data ranged from January 2019 to September 2023. Based on this, we evaluated only the common date range (ending September 2023) for our subsequent analysis.

Data Analysis Approach

Once our datasets were prepped and merged, we could begin our analysis. Our high level methodology can be found below. These steps will be discussed in more detail in the sections that follow, along with plots and figures to illustrate our findings:

1. Examine national trends in trips per capita vs. percent of remote work jobs.
2. Compare states based on number of trips per capita and percent of remote work jobs.
3. Compare regional trends in trips per capita between the different time periods surrounding of COVID-19 (before, during, and after).
4. Examine the relationship between trips per capita and percent of remote job postings, and how that changed over time, at both the national and state level.

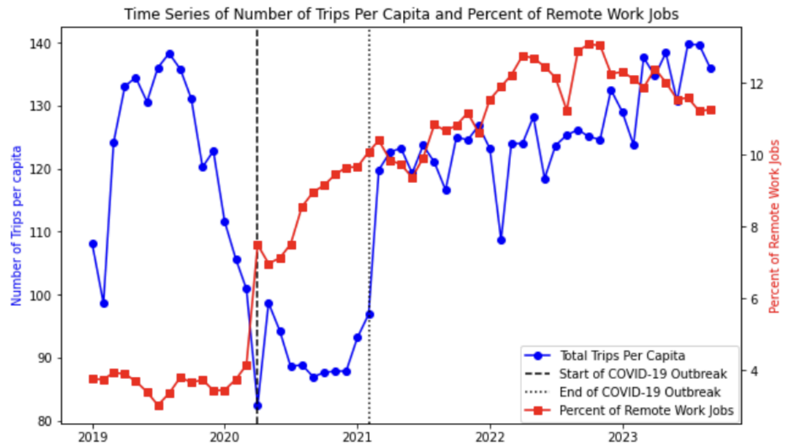
Key Assumptions

- Average population across the entire time period was used for per capita calculations.
- COVID period is defined as April 1st, 2020 until February 1st, 2021 (with justification provided in later sections).
- Trips data is sampled using a multi-level weighting method to reduce bias and be representative of the entire population for the state or nation (Titlow, 2020).

Data Analysis and Findings

National Level Trends

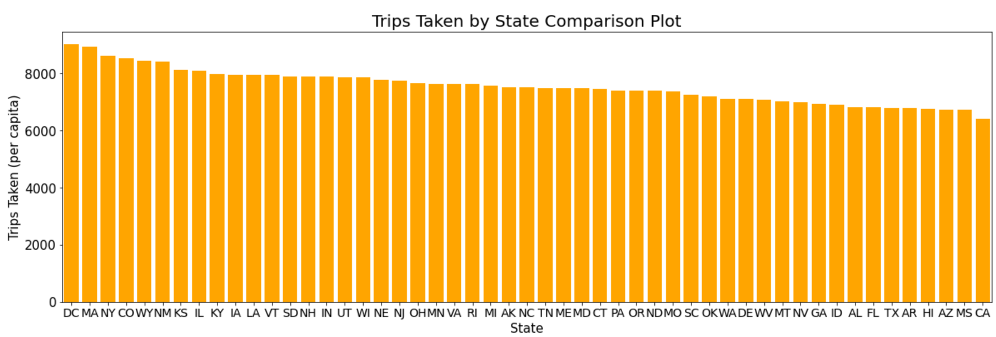
We began our analysis by plotting the number of trips per capita as a time series against the percent of remote work jobs, at the national level. One of the key questions in our analysis is whether the number of postings in a given state have any impact on people's travel habits, and we wanted to determine if there was a correlation between the two variables at a national level. By plotting this over time, we could identify whether inflection points occurred at key dates related to the COVID-19 pandemic.



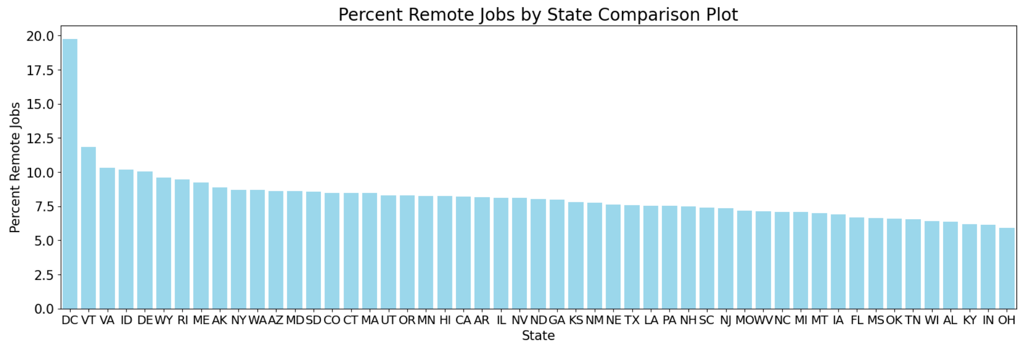
From the above chart it is clear that total trips per capita declined at the start of the COVID-19 outbreak, while the percent of remote work jobs saw a sharp increase. Remote work jobs climbed steadily throughout the COVID-19 outbreak, while total trips per capita remained low, until the end of the period as states lifted their lockdown restrictions. In the period following COVID-19, the number of trips per capita rebounded as people got back to their normal lives, although it did not reach pre-pandemic levels until the end of 2023. Interestingly, remote jobs continued to rise at the same rate as during the pandemic for nearly 2 years, eventually peaking toward the end of 2023 and declining slightly since then.

State Level Comparison

We continued our analysis by next examining a comparison of trips taken by state. Due to the differences in populations between states, we chose to evaluate this on a per capita basis, since that would be a more accurate reflection of an individual's travel habits. By rank ordering the states as shown below, we were able to clearly compare each state against one another. We identified the top states as DC, MA, and NY, and the bottom states as CA, MS and AZ for trips taken per capita.



We then compared the states based on percent of remote jobs, in order to determine which states were most and least likely to offer remote work. Since the percent of remote jobs for each state varied over time, we took the average across the entire date ranges for this comparison. In subsequent sections we will examine the time series behavior for certain states, but an average will suffice for this initial comparison.

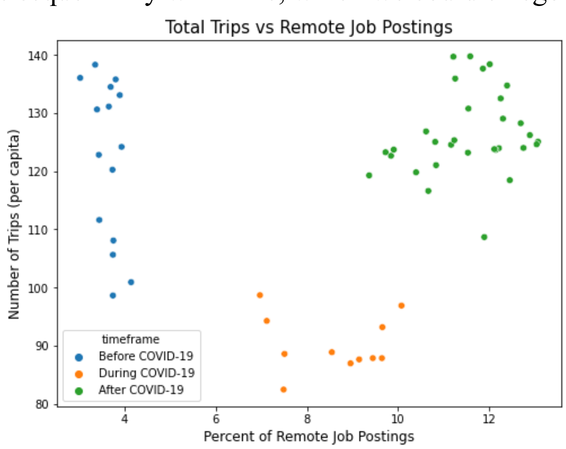


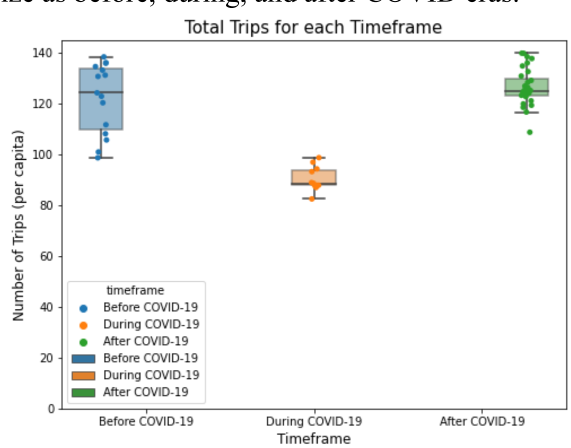
From the above chart, we can see that the top states are DC, VT, and VA, while the bottom states are OH, IN, and KY for percent of remote jobs. DC in particular is a significant outlier compared to the rest of the states, in addition to being the top state in trips per capita. Based on these comparisons, we have a better understanding of which states might be interesting to examine in further detail. In particular, the top states for each chart will be analyzed in more detail in the sections that follow.

Defining COVID-19's Impact

As observed in the previous section, COVID-19 had a significant impact on the percent of work from home jobs as well as the number of trips between the two. However, to see the impact that it played on an individual state basis we first needed to define a time frame when COVID-19 began and ended.

We began this investigation by plotting the relationship between the Total Number of Trips per capita against the percent of remote job postings, as shown in the left scatter plot below. Each datapoint on the scatter plot is a different month of data. Through the plot, we recognized that there were three distinct groups of data. When we categorized the months by these groupings, we realized that the groups came sequentially with time, which we could categorize as before, during, and after COVID eras.





The blue in the plot was defined as the time period before April 1st, 2020, the orange points is the timeframe from April 1st, 2020 until February 1st, 2021, and the green points are any dates post February 1st, 2021. Some insights we can gain from this plot is that even after COVID concluded, the percent of remote jobs throughout the country continues to grow, indicating that corporate culture has adapted to the lifestyle brought by COVID. We can further validate our assumptions by reviewing the date when lockdowns began, which was on March 12th, 2020 and we can assume that the number of trips took the second half of March to fully adjust to the lockdowns (Jacobsen, 2020). We can also assume that the impact of COVID-19 subsided in February 2021 because although most restrictions on states ended around August 2020, the number of new COVID-19 cases continued to climb until the peak during January 2021, due to the evolution of new variants (Lee, 2021).

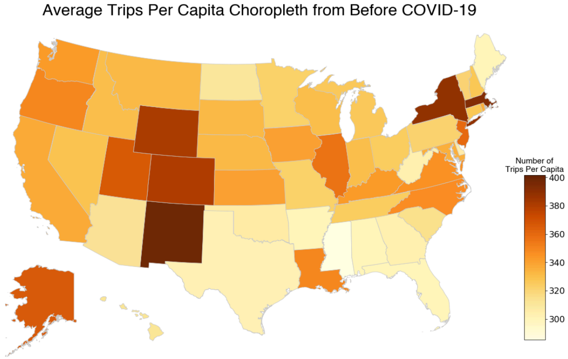
Furthermore, the box plot to the right of the scatter plot above compares the total number of trips for each time period, where it delineates the number of trips people have taken before, during, and after COVID-19. We can see that the median for pre and post COVID-19 are very similar to another, suggesting that we have returned back to normalcy in our travel habits, although the lower quartile has shifted up for the post COVID-19 data.

Evolution of Travel Habits due to COVID-19

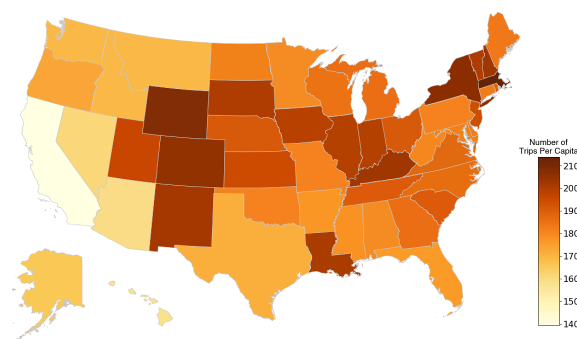
Now that we have validated and found concrete months for the start and end of the effects of the coronavirus, we can also look on a state level through the use of a choropleth, or a geographical heatmap, with the shapely.geometry and geopandas modules (Rich, 2023). The heatmaps below show the evolution of the average number of trips per capita before, during, and after the coronavirus pandemic.

One observation to note is that the data post COVID has the most number of months and so we expect the average number trips during this time period to be the highest. What we are most interested in from this plot is not the magnitude of what the colors represent, however, what we hope to analyze is the relative change between states over time. Also, Washington D.C. is not visualized in this plot, but will be explored in the following sections.

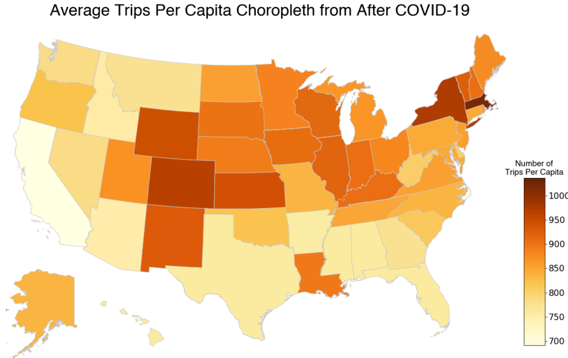
Average Trips Per Capita Choropleth from Before COVID-19

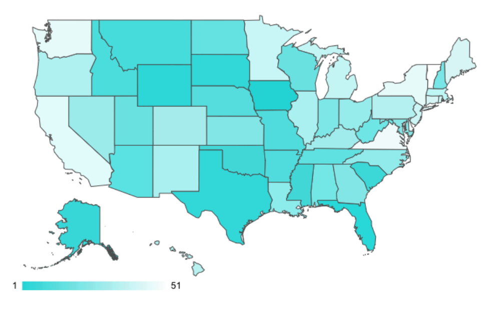


Average Trips Per Capita Choropleth During COVID-19



Average Trips Per Capita Choropleth from After COVID-19

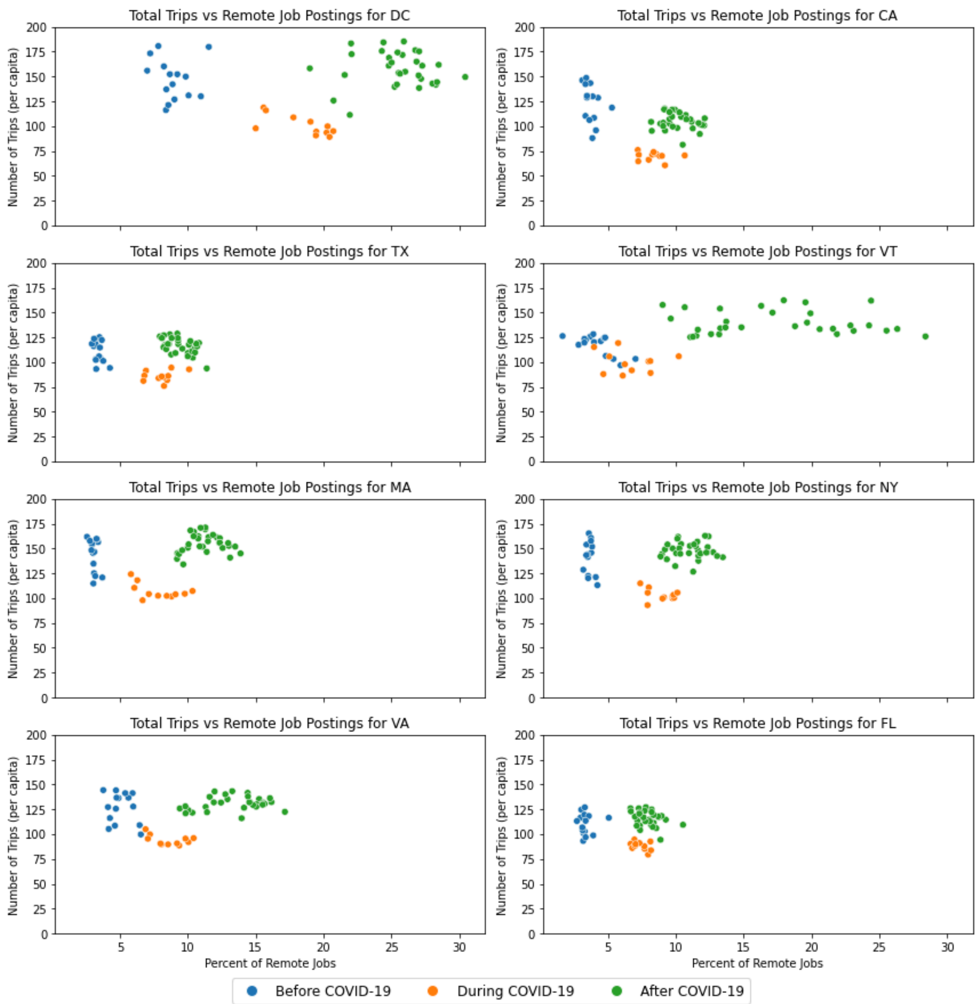




States with the Fewest COVID-19 Restrictions

One insight that can be derived from the choropleths is that states like California had a nominal number of trips prior to COVID-19; however, during COVID-19, the state had one of the lowest travel rates, which continued once COVID-19 ended. This observation can also be applied to several states in the western region. On the contrary, the southern part of the United States tended to travel more than other states, specifically during the COVID-19 period. The above blue graph was taken from a WalletHub article (McCann, 2021) and shows a heatmap of the states with the fewest number of restrictions during COVID-19, where fewer restrictions is indicated as a higher rank and a darker shade in color. We can correlate the above heatmap with our current one as we can see that California was ranked as one with the most restrictions, while many of the states in the south were ranked much higher. As a result, we can see that the number of restrictions did seem to dictate people's tendency to travel, as one might expect. However, this observation is not perfect, where Vermont was ranked as the state with the highest number of restrictions but also had the most number of trips during the COVID-19 time period.

Finally, we reviewed the scatter plot of number of trips per capita to the percentage of work from home jobs on a state level, coloring by whether the data was before, during, or after COVID-19. We chose eight states in particular because they showed up as the top three states in each of our bar graphs above, where [DC, MA, NY] were the states with the highest number of trips per capita, [DC, VT, and VA] had the highest percentage of remote work job postings, and [CA, TX, and FL] were the three states that had the highest population. In this respect, we can see how many different states traveled in response to the percentage of remote work jobs.



Looking at the overall plot, we can see that most states had a distinct transition of percent remote work job postings since the beginning of COVID-19. This does not apply, however, to Vermont, and to a lesser extent Virginia, which slowly grew into the remote work from home lifestyle but fully adopted the lifestyle and shot past many other states in the percent of remote work jobs after COVID-19 stabilized. DC, on the other hand, was a leader in both number of trips per capita and percentage of job postings, which is also seen in the plot below. We can see that even prior to COVID-19, DC had nearly double the percentage of remote job postings than any other state, which only grew during and after the pandemic. This could be due to a multitude of factors, such as the fact that DC is home to many politicians, who travel in and out of the area on a constant basis.

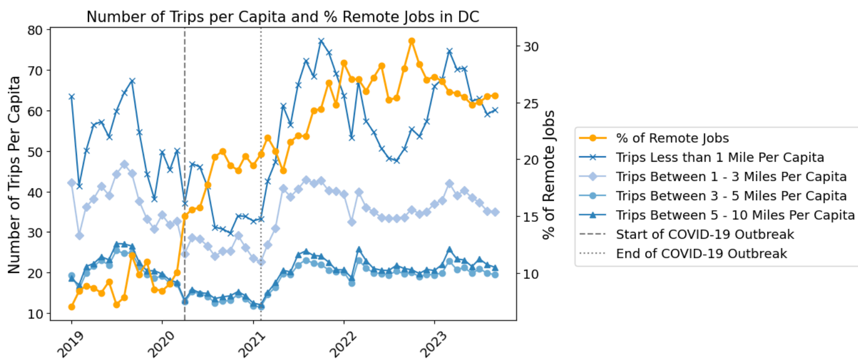
Ultimately, from this plot and when we reviewed it on a national level, there does not seem to be a correlation between the number of trips and the percentage of remote jobs, even after COVID ended. This can be viewed through Vermont and DC, where although the number of remote jobs increased overall after COVID, the number of trips remains relatively stable. And when looking at other states such as California, Florida, New York, and Texas, they all tell a similar story that the number of trips did not increase after the pandemic, but returned back to normal pre-pandemic levels, even though the percentage of remote jobs continued to increase. And specifically for Florida and California, the percentage of remote jobs did not actually change as much after the pandemic.

State Review: DC

As previously mentioned, Washington, D.C., stood out as the region with both the highest trips taken per capita and the highest percentage of remote jobs in the country. An analysis was conducted using three distinct plots, each representing various travel distances categorized as short, medium, and long.

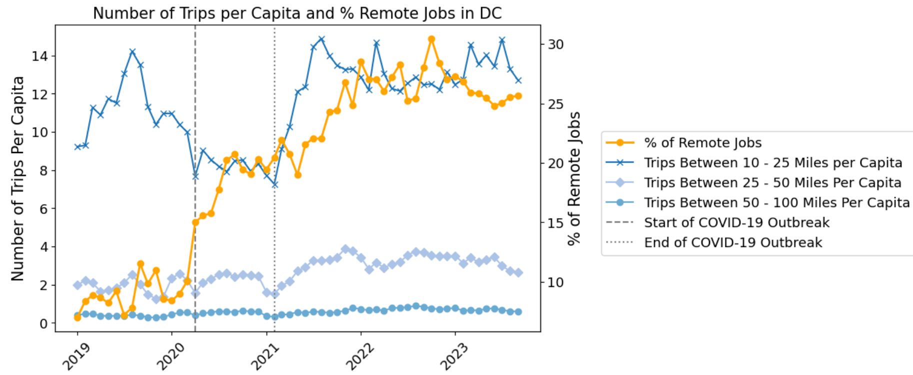
<u>DC - Short Travel Distance:</u>

The plot for short travel distances showcases how the percentage of remote jobs affects the number of short-distance trips per capita, spanning from under 1 mile to a maximum of 10 miles. We can see a significant drop in the number of short trips during the COVID-19 lockdown as the percentage of remote jobs rose. As the lockdown eased, the number of trips increased as people resumed their usual routines. Even after the pandemic, the percentage of remote jobs continued to rise, but it leveled off towards the end of 2022.



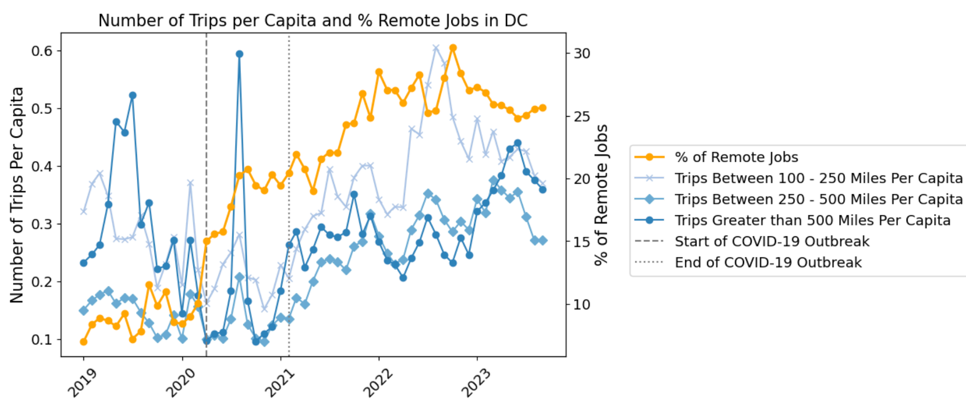
<u>DC - Medium Travel Distance:</u>

The medium travel distance plot focuses on travels spanning distances between 10 and 100 miles. Here, we observe a distinct relationship where an increase in remote job postings coincides with a decrease in medium-distance trips per capita during the COVID-19 lockdown. This correlation might reflect the reduced need for traditional commuting, as more people work from home, thus reducing their overall travel for professional purposes. However, after the pandemic, the number of trips increased, similar to what we observed in the short travel distance plot.



DC - Long Travel Distance:

The plot for long-distance trips in Washington D.C., which includes travel from 100 miles up to those exceeding 500 miles, reveals interesting fluctuations. Notably, there's a significant spike in August 2020. During this spike, many states were lifting COVID-19 restrictions, leading to a sudden increase in travel as businesses reopened and mask mandates were lifted (The New York Times, 2021). People took advantage of the opportunity to travel long distances, but it was short-lived. With COVID-19 cases on the rise again, authorities reintroduced restrictions, resulting in a decline in long-distance trips after August 2020. Even though there was a temporary surge, the main trend in the plot matches what we've seen with short and medium travel distances.



State Review: CA

Similar to Washington D.C., California's travel data offers insights into the effects of remote work on travel habits. We analyzed the data across short, medium, and long travel distances, with these plots displayed in Appendix A5.

Both California and Washington D.C. exhibit variations in trips per capita and the percentage of remote jobs. For instance, from 2019 to 2023, Washington D.C. recorded a higher frequency of trips under one mile per capita, ranging from 40 to 75 trips. In contrast, California's figures for the same distance were lower, spanning from 15 to 40 trips per capita. Conversely, for distances between 10 to 25 miles, California observed more trips per capita, with figures between 10 and 20, while Washington D.C. had between 7 and 15. In terms of remote jobs, Washington D.C. saw an increase in the percentage after 2022, reaching about 25% to 30%, whereas California's percentage remained between 8% and 12%.

Despite these differences, the overall trend patterns in both California and Washington D.C. were consistent: the number of trips per capita decreased as the percentage of remote jobs increased during the pandemic, but rebounded to pre-pandemic levels afterward. Moreover, both states experienced a modest spike in trips over 500 miles per capita in August 2020, though it was less pronounced in California. Further investigation would be needed to understand why Washington D.C. experienced a more significant peak in August 2020 compared to California.

Conclusions

Overall, the WFH and Trips dataset analysis highlights two key conclusions toward answering our research questions. The first conclusion is that COVID-19 had a significant impact on both the number of trips that people take and the percentage of remote job postings, which can be observed on both the state and the national level. The second conclusion we can infer is that there is no relationship between the percentage of WFH jobs and the number of trips that a person takes. This applies to both the national and state level comparisons as well as on the length of the trips taken.

Alluding to point one, we observed that with any given state, there was a distinct downward step change in the number of trips that an individual traveled and a distinct upward step change in the percent of remote jobs during the period of April 2020 until February 2021. This makes sense as the coronavirus effectively locked down the whole world and prevented people from traveling and working. Following the lockdown period, we observed that the number of trips quickly responded with a shift in the number of trips taken for all lengths of trips.

However, in reference to conclusion two, the interesting trend is what happened after the COVID-19 era, where the number of remote jobs continued to climb even to this day. This suggests that remote work is here to stay and that COVID allowed corporations to realize the benefits to this new lifestyle. Even with this abundance of remote work opportunities, we showed that this did not change a person's tendency to travel. Nearly all states and the entire nation as a whole showed that after COVID-19, the number of trips only returned back to pre-pandemic levels (and did not increase or decrease), delineating that WFH does not play a factor in our travels.

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Appendix

A.1. Table of Column names from our Trips dataset:

Column Name	Description	Type
Level	Indicates National, State, or County level metrics	object

Date	Date	object
State FIPS	Two-digit FIPS state code	object
State Postal Code	State postal code	object
County FIPS	Five-digit FIPS county code	object
County Name	County name	object
Population Staying at Home	Number of residents staying at home, i.e., persons who make no trips with a trip end more than one mile away from home	int64
Population Not Staying at Home	Number of residents not staying at home	int64
Number of Trips	Number of trips made by residents, i.e., movements that include a stay of longer than 10 minutes at an anonymized location away from home.	int64
Number of Trips <1	Number of trips by residents shorter than one mile	int64
Number of Trips 1-3	Number of trips by residents greater than one mile and shorter than 3 miles ($1 \leq$ trip distance < 3 miles)	int64
Number of Trips 3-5	Number of trips by residents greater than 3 miles and shorter than 5 miles ($3 \leq$ trip distance < 5 miles)	int64
Number of Trips 5-10	Number of trips by residents greater than 5 miles and shorter than 10 miles ($5 \leq$ trip distance < 10 miles)	int64
Number of Trips 10-25	Number of trips by residents greater than 10 miles and shorter than 25 miles ($10 \leq$ trip distance < 25 miles)	int64
Number of Trips 25-50	Number of trips by residents greater than 25 miles and shorter than 50 miles ($25 \leq$ trip distance < 50 miles)	int64
Number of Trips 50-100	Number of trips by residents greater than 50 miles and shorter than 100 miles ($50 \leq$ trip distance < 100 miles)	int64
Number of Trips 100-250	Number of trips by residents greater than 100 miles and shorter than 250 miles ($100 \leq$ trip distance < 250 miles)	int64
Number of Trips 250-500	Number of trips by residents greater than 250 miles and shorter than 500 miles ($250 \leq$ trip distance < 500 miles)	int64
Number of Trips >=500	Number of trips by residents greater than 500 miles (trip distance ≥ 500 miles)	int64
Row ID	Unique row identifier	object

Week		int64
Month		int64

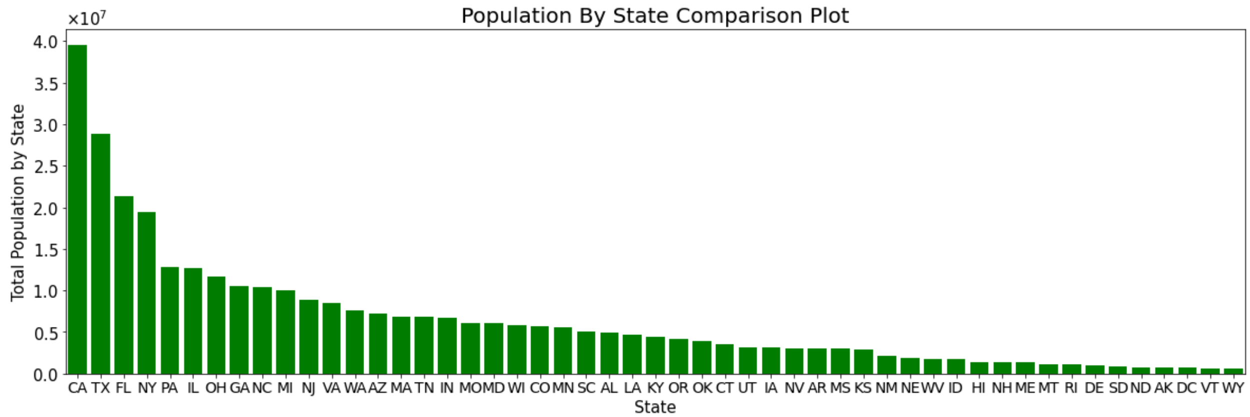
A.2. Table of Column names from our WFH dataset:

Column Name	Description	Type
Year	Year that the data was taken	int64
Month	Month that the data was taken	object
Year Month	A floating point number where the whole number in front represents the year and the decimal represents the percent of the year that the data was taken.	float64
State	Full name of the state	object
Region	Region of the state (South, West, Midwest, Northeast)	object
Division	Division of the state (South Atlantic, Mountain, West North Central, New England, Pacific, East North Central, West North Central, West South Central, East South Central, Middle Atlantic)	object
State Code	Shortened two letter abbreviation of state	object
Percent	Percent of remote jobs	float64
N	Number of total jobs	int64
Measurement	How the data was measured (all are 1 Month Averages)	object

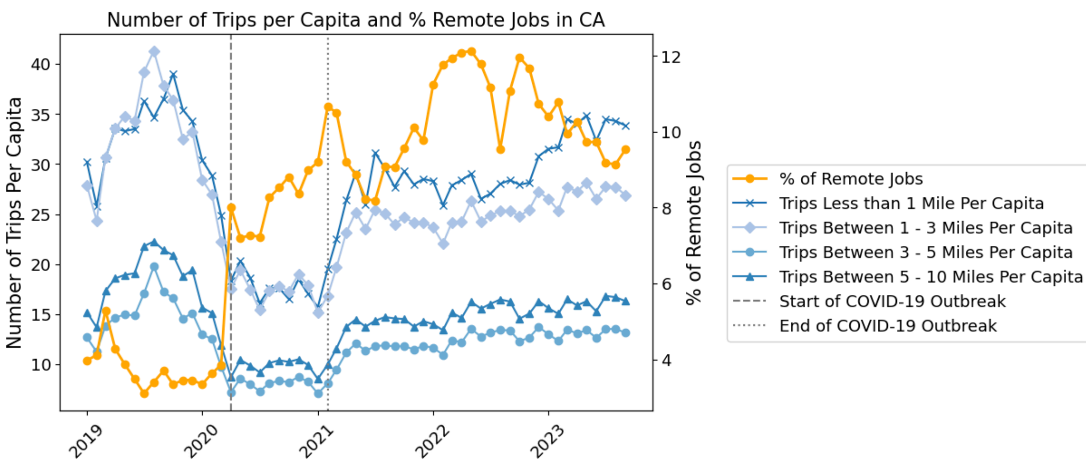
A.3. groupby function to average the total population and average all other trips columns:

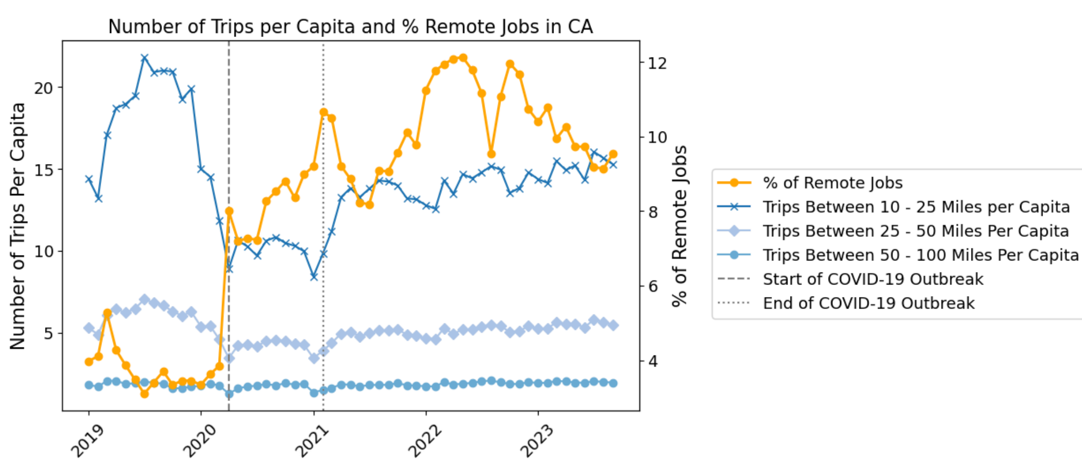
```
def sum_mean(column):
    if column.name == 'total_population':
        return column.mean()
    else:
        return column.sum()
grouped_df = state_trips_df.groupby([‘month_year’,'state_code']).agg(sum_mean)
```

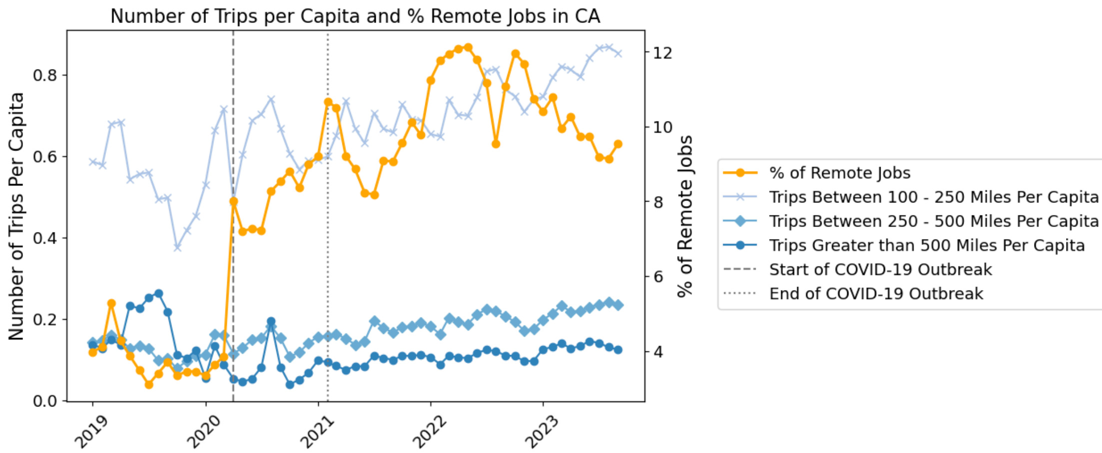
A.4. Population by State:



A.5. CA - Short, Medium, and Long Travel Distance Plots:






Number of Trips per Capita and % Remote Jobs in CA
Number of Trips Per Capita
% of Remote Jobs
0.0
0.2
0.4
0.6
0.8
4
6
8
10
12
2019
2020
2021
2022
2023
% of Remote Jobs
Trips Between 100 - 250 Miles Per Capita
Trips Between 250 - 500 Miles Per Capita
Trips Greater than 500 Miles Per Capita
Start of COVID-19 Outbreak
End of COVID-19 Outbreak