Urban Transportation in the United States During the COVID-19 Pandemic

Anthony P. Borgese

University of Pennsylvania

Follow this and additional works at: https://repository.upenn.edu/wharton_research_scholars

Part of the Infrastructure Commons, Public Economics Commons, Regional Economics Commons, Transportation Commons, and the Urban Studies Commons

https://repository.upenn.edu/wharton_research_scholars/222

This paper is posted at ScholarlyCommons. https://repository.upenn.edu/wharton_research_scholars/222
For more information, please contact repository@pobox.upenn.edu.
Urban Transportation in the United States During the COVID-19 Pandemic

Abstract
This paper aims to perform initial research into transportation patterns in the continental U.S. during the COVID-19 pandemic. In order to do this, I will apply methods from previous research on data collected during the pandemic era, and then compare this to pre-COVID data to see if there are any relevant conclusions. This research would allow us to see how cities in the U.S. have responded to the COVID crisis in terms of urban mobility, and if there are lessons to be learned for future pandemics. With initial observations, the most reasonable conclusion to draw is that, although COVID-19 has impacted transportation, along with most other areas of life in the U.S., that these changes in transportation patterns do not change the fundamental predictors of urban mobility that we have seen in previous research. Although specific data points and overall measures of travel characteristics may change, many of the underlying patterns remain roughly the same.

Keywords
transportation, urban, covid, pandemic, transportation patterns, urban mobility

Disciplines
Infrastructure | Public Economics | Regional Economics | Transportation | Urban Studies
Urban Transportation in the United States during the COVID-19 Pandemic

By

Anthony Borgese

An Undergraduate Thesis submitted in partial fulfillment of the requirements for the

WHARTON RESEARCH SCHOLARS

Faculty Advisor:

Gilles Duranton

Dean's Chair, Real Estate

THE WHARTON SCHOOL, UNIVERSITY OF PENNSYLVANIA

MAY 2021
Abstract: This paper aims to perform initial research into transportation patterns in the continental U.S. during the COVID-19 pandemic. In order to do this, I will apply methods from previous research on data collected during the pandemic era, and then compare this to pre-COVID data to see if there are any relevant conclusions. This research would allow us to see how cities in the U.S. have responded to the COVID crisis in terms of urban mobility, and if there are lessons to be learned for future pandemics. With initial observations, the most reasonable conclusion to draw is that, although COVID-19 has impacted transportation, along with most other areas of life in the U.S., that these changes in transportation patterns do not change the fundamental predictors of urban mobility that we have seen in previous research. Although specific data points and overall measures of travel characteristics may change, many of the underlying patterns remain roughly the same.
Introduction:

My research question surrounds the effects of COVID-19 on urban transportation in the United States. With the COVID pandemic, many areas of life have been affected by the lockdown order, transportation being among one of the largest of these areas. In this paper, I will attempt to review the research that has already been done in this area, specifically research that has been done on transportation patterns in urban areas in the U.S. from 1995 to 2017, while applying this research and its methods to newer data from the COVID pandemic era to try to draw apt conclusions and relevant comparisons to previous studies.

Although COVID-19 has definitely had a strong global impact on many areas of life, including transportation, we do not think that it has impacted urban transportation patterns in the U.S. as much as it may seem upon initial observations. Previous urban transportation research has found that much of the difference in speeds between different urban areas comes not from the actual congestion and different levels of traffic between cities, but rather from the difference in base uncongested speeds that we observe in these areas and the factors that make up this uncongested difference. I theorize that this fundamental observation has not changed in times of COVID; although specific observations or data trends may change slightly, we expect to see many of the same patterns in urban transportation that we saw before the pandemic era began to impact the U.S.

In terms of research motivation, a few types of experts who could find this research informative are disease experts and urban planners. Disease experts could use this information to structure policies around COVID. Elements such as the fear of public transportation and how this may affect crowds on transit, number of people staying home, and the creation of new
transportation hotspots as people shift their preferences more towards private transportation are all factors we must consider as we move forward in the world of COVID. Especially as we have just recently started distributing vaccines, these may all be categories that are about the change.

The second major category of people to find this research useful is urban planners. In analyzing travel patterns during COVID, urban planners could use this data to better understand how different kinds of transportation systems and structures within cities have traditionally functioned and how this has changed since the beginning of the COVID pandemic. Although they may have general data on the amount that different types of transportation has been used, planning for the rest of the pandemic and other future crises may require more in depth analysis than what is currently available.

Next, understanding how different transportation systems have handled the crisis and how congestion and other factors will change moving forward is also valuable information. There are many complex factors that will ripple through the system. For example, less use of public transit may increase highway congestion in the near future and create newer hotspots of congestion, especially around office buildings and other places of work. An implication of this may be that we should build more highway lanes near these places of congestion, or build more parking near these areas. These are just a few ways that understanding transportation patterns in COVID may help us deal with potential problems in the future.

**Literature review:**

When analyzing transportation in the U.S., all areas have been hit hard, but it seems that public transportation has been hit the hardest, as shown in the figure below. This has been in part due to reduced amounts of service available, but also because of public perception of public
transit as more dangerous because of closer, potentially unavoidable, contact with others that may spread the virus. This is due to the potential two-week incubation period of the virus increasing uncertainty, many surfaces on which to spread the virus, and official guidelines advising against the use of public transportation, among others.

Looking at private transportation, we can see that it has rebounded faster than use of public transportation. According to the National Academies of Sciences, Engineering, and Medicine, compared to 2019 transportation levels, passenger car travel went down by 77% in April 2020, but by the end of July 2020 was only down by 11% from 2019 levels. With this rebound in private transportation, it seems reasonable that people will rely on it over public transportation as the pandemic progresses. Despite this, the largest variable to consider moving forward will likely be the rate at which people return to using public transit, now that an effective vaccine is available. It also remains to be seen how the holiday season will affect travel during COVID; it seems that the total number of trips for the holidays in the U.S. decreased, but the number of long distance trips increased (Smallen). Whether this will significantly impact infection rates is still unclear.

Some studies (Hu, Lin, Wang) have shown that with increasing distance between passengers and sufficiently decreased travel time per passenger, risk of infection can be significantly decreased. This does not eliminate the remaining psychological factors that must be taken into account. Since most of the public may not be aware of the relevant research, it might not have significant effects on the public’s perception of and use of public transportation.

We can also try to estimate how the release of the vaccine may impact transportation. In a recent Penn LDI seminar, several professionals working on the vaccine and its distribution gave
an overview of the possibilities moving forward. There is probably going to be significant lag in
the effects this will have on people’s confidence and behavior, as it will take a while to both
assess the vaccine’s effectiveness and produce and distribute the vaccine to the majority of the
population. As we do not have data for transportation during the vaccine’s release, this research
will have to wait.

Other factors that might contribute to this lag include the percentage of the population
that gets vaccinated and whether herd immunity can be achieved, the possibility of waning
immunity to the virus despite vaccination that may necessitate periodic booster doses, viral
mutations that may necessitate booster doses similar to that seen with the flu shot, and the
general public's receptiveness to booster shots. In addition, we must consider the likelihood of
more remote work and virtual meetings, along with the reduced role and value of office space
and decreased importance of business travel.

The research suggests that many changes we have experienced during the crisis will
remain in place for longer than the pandemic itself, in many different areas. This is in part due to
the fact that research surrounding many of the changes made to daily commutes for many
professionals show that they may remain flexible or completely online even moving past the
crisis (Chandra). In addition, fear of public transportation as discussed above may also keep
many members of the public off of public transit for a significant period of time, which in turn
may create new congestion points on freeways and highways near office buildings and important
public centers (Chandra).
Methods:

I reference two papers specifically that provide the basis for most of my current research. The first paper (Couture, Duranton, Turner) outlines a previously tested and reliable methodology for creating city-level supply curves for travel. This is the first instance of a sound measure of the efficiency with which different locations produce transportation. Using these curves, the paper created travel speed indices for each of the major U.S. cities using household survey data. It also examines different city structures, the effects they have on congestion, and the returns to scale of each of these structures.

For example, we find that dense and centralized cities have a lower average vehicle speed than cities with ring roads. Furthering this kind of investigation may provide more insights into the designing of cities for more efficient travel. Below is a sample table describing the speed of the five fastest and five slowest cities in different years to demonstrate the results of this research.

The second paper directly pertaining to my research (Akbar, Couture, Duranton, Storeygard) concerns the use of counterfactual trip instances to create indices similar to those in the previous paper. The difference is in the sourcing of the data. The data in this paper is in terms of trips collected from Google Maps. Collecting this data for 154 Indian cities led the authors to a few conclusions. Uncongested mobility and congestion may seem to be directly related, but there are actually differences between them. Below is sample output for some of these indices.
Fig. 1: Log trip speed determinants from previous paper

Overall, these methods of research open up a few different options to create the indices and trip measures required to perform research. Our goal is to recreate this research with data obtained during the COVID era and compare before and after in order to see the effects and create a prediction for how to deal with congestion and COVID in the near future. When analyzing this data, we will likely have to focus on only a few variables at first, such as time of day of work trips to analyze changes in rush hour timing. After we perform this initial analysis, we will have to modify our hypothesis in order to better understand the data.
Data:

Initial observations:

For my data analysis, I used a dataset composed of locations entirely in the 48 states of the continental United States. After parsing through the data and dropping observations that were duplicates and/or contained inaccurate or missing data values, I created my main dataset. From this, I had a selection of 264 distinct counties or Metropolitan Statistical Areas (MSAs), with about 460,000 unique trips in my master dataset. In this case, a trip is defined as a set of points, one origin and one destination point, with each trip taken at a particular time referred to as a trip instance.

Running some initial analyses on the date, I found a few interesting phenomena. Below is one of the first graphs I ran showing the mean speed of all trips on any given day in the dataset, with the days ranging from March 13-31. Given that March 13 was the beginning of pandemic status in the U.S., the fact that the speeds of trips remained practically constant was surprising. One would think that the lack of congestion after the beginning of COVID restrictions would significantly impact travel speeds. Therefore, I decided to delve deeper into this to try to see if there were striking differences over this time period in other measures.
Next, I attempted to examine the change in mean speeds over different times of day. The graph below separates trips into the hour of day they occurred, with 0 corresponding to trips taken between midnight and 1AM, 1 corresponding to trips between 1am and 2am, etc. The results make sense upon an initial examination, with the lowest speeds corresponding to the most congested periods during peak hours from roughly 12pm to 4pm. If we compare this to results from previous studies, as in Fig. 4, we can see that our result closely matches that of previous studies.
Fig. 3 Mean travel speeds over time of day

Fig. 4. Mobility comparison from Akbar et al.
However, there are many smaller effects that we also want to examine. We want to see more specific differences between cities and travel characteristics within them, both purely during the COVID pandemic itself and between the pandemic and earlier studies.

**Differences in impact within cities:**

One of the first things we hypothesize is that the mobility inside major cities and denser areas will see the most changes during the time period outlined in our dataset than will less dense, uncongested areas, as the change in congestion will probably be the highest.

However, there is also a strong possibility that this will not be the case. As we have seen in previous studies, such as Akbar et al., most of the differences in mobility in cities actually comes from variations in uncongested rather than congested mobility. This means that in general, the slower cities are much slower on average during all times than cities that tend to be faster, even in times that the slower cities are uncongested. The COVID pandemic will not likely alter this fundamental feature that we have observed in previous studies: however, we do want to see exactly how much and in what ways COVID has altered patterns in urban areas, specifically concerning congested and uncongested mobility.
In order to determine what is actually the case, I created speed indices for the dataset as a whole and for specific locations, also referring to Table A.3 of Couture et al. Below is the summary information for basic trip information of the master dataset as a whole. As we can see, over the 458,895 observations in the dataset, the mean trip distance is ~15.16 km, with average congested trip times of ~14 minutes and uncongested trip times of ~13.54 minutes. However,
after modifying the data by removing outlier observations (in this case, observations over one standard deviation away from the mean in terms of trip time, along with trips less than 5 km or greater than 10 km, for ease of comparison to previous research) we obtained a more condensed dataset with only 105,546 observations, with a mean trip distance of ~7.18 km and mean uncongested trip times of ~9.24 minutes and congested trip times of ~9.57 minutes.

Fig. 6 Summary of trip characteristics

Using both of these datasets, I then created average speed measures for individual MSAs in order to compare them to each other and to average trips as they are defined above. As we can see, the average uncongested speeds of both datasets are roughly similar to the congested speeds, which tells us that actual congestion in the cities represented in this dataset still does not play a huge role in corresponding average speeds we witness in this data, but rather that these differences are due to other, fixed effects in these cities.
Below I took a select sample of 20 of the largest MSAs in the U.S., which are ranked from slowest to fastest in terms of mean speed. Comparing them to previous rankings of MSAs in terms of congestion and speed, we see rough similarities in the rankings of cities from previous papers. The cities sampled below are the ones that tended to affect the data most, whether it be from the number of datapoints contributed or from the congestion effects.

<table>
<thead>
<tr>
<th>county</th>
<th>meanspeedcounty</th>
</tr>
</thead>
<tbody>
<tr>
<td>Miami-Fort Lauderdale-West Palm Beach, FL MSA</td>
<td>44.15531</td>
</tr>
<tr>
<td>Seattle-Tacoma-Bellevue, WA MSA</td>
<td>45.92983</td>
</tr>
<tr>
<td>Chicago-Naperville-Elgin, IL-IN-WI MSA</td>
<td>46.14445</td>
</tr>
<tr>
<td>San Francisco-Oakland-Berkeley, CA MSA</td>
<td>46.97585</td>
</tr>
<tr>
<td>Tampa-St. Petersburg-Clearwater, FL MSA</td>
<td>47.07143</td>
</tr>
<tr>
<td>New York City-Newark-Jersey City, NY-NJ-PA MSA</td>
<td>47.19501</td>
</tr>
<tr>
<td>Denver-Aurora-Lakewood, CO MSA</td>
<td>47.69898</td>
</tr>
<tr>
<td>Boston-Cambridge-Newton, MA-NH MSA</td>
<td>47.82816</td>
</tr>
<tr>
<td>Washington-Arlington-Alexandria, DC-VA-MD-WV MSA</td>
<td>48.18193</td>
</tr>
<tr>
<td>Philadelphia-Camden-Wilmington, PA-NJ-DE-MD MSA</td>
<td>48.46948</td>
</tr>
<tr>
<td>Los Angeles-Long Beach-Anaheim, CA MSA</td>
<td>48.64368</td>
</tr>
<tr>
<td>Houston-The Woodlands-Sugar Land, TX MSA</td>
<td>48.97475</td>
</tr>
<tr>
<td>San Diego-Chula Vista-Carlsbad, CA MSA</td>
<td>50.16334</td>
</tr>
<tr>
<td>Dallas-Fort Worth-Arlington, TX MSA</td>
<td>50.95956</td>
</tr>
<tr>
<td>Atlanta-Sandy Springs-Alpharetta, GA MSA</td>
<td>51.48391</td>
</tr>
<tr>
<td>Phoenix-Mesa-Chandler, AZ MSA</td>
<td>51.68172</td>
</tr>
<tr>
<td>Charlotte-Concord-Gastonia, NC-SC MSA</td>
<td>52.05084</td>
</tr>
<tr>
<td>St. Louis, MO-IL MSA</td>
<td>52.29271</td>
</tr>
<tr>
<td>Detroit-Warren-Dearborn, MI MSA</td>
<td>52.3931</td>
</tr>
<tr>
<td>Minneapolis-St. Paul-Bloomington, MN-WI MSA</td>
<td>56.17369</td>
</tr>
</tbody>
</table>

Fig. 7  20 largest MSAs in 2019, ranked slowest to fastest average speed
<table>
<thead>
<tr>
<th>cityname_corrected</th>
<th>state</th>
<th>city_cong_factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rapid City, SD MSA</td>
<td>SD</td>
<td>0.083281</td>
</tr>
<tr>
<td>Colorado Springs, CO MSA</td>
<td>CO</td>
<td>0.0751082</td>
</tr>
<tr>
<td>Casper, WY MSA</td>
<td>WY</td>
<td>0.0734366</td>
</tr>
<tr>
<td>Cheyenne, WY MSA</td>
<td>WY</td>
<td>0.0707680</td>
</tr>
<tr>
<td>Great Falls, MT MSA</td>
<td>MT</td>
<td>0.0660051</td>
</tr>
<tr>
<td>Tuscaloosa, AL MSA</td>
<td>AL</td>
<td>0.0619403</td>
</tr>
<tr>
<td>Muncie, IN MSA</td>
<td>IN</td>
<td>0.0594372</td>
</tr>
<tr>
<td>Alexandria, LA MSA</td>
<td>LA</td>
<td>0.0540086</td>
</tr>
<tr>
<td>Steubenville-Weirton, OH-WV MSA</td>
<td>OH</td>
<td>0.0530536</td>
</tr>
<tr>
<td>Sioux City, IA-NE MSA</td>
<td>IA</td>
<td>0.0521368</td>
</tr>
<tr>
<td>Altoona, PA MSA</td>
<td>PA</td>
<td>0.052068</td>
</tr>
<tr>
<td>State College, PA MSA</td>
<td>PA</td>
<td>0.051588</td>
</tr>
<tr>
<td>Pine Bluff, AR MSA</td>
<td>AR</td>
<td>0.0508338</td>
</tr>
<tr>
<td>Jackson, MS MSA</td>
<td>MS</td>
<td>0.0507421</td>
</tr>
<tr>
<td>Decatur, IL MSA</td>
<td>IL</td>
<td>0.0505074</td>
</tr>
<tr>
<td>Lubbock, TX MSA</td>
<td>TX</td>
<td>0.050283</td>
</tr>
<tr>
<td>Erie, PA MSA</td>
<td>PA</td>
<td>0.0501018</td>
</tr>
<tr>
<td>Fort Walton Beach, FL MSA</td>
<td>FL</td>
<td>0.0497389</td>
</tr>
<tr>
<td>Monroe, LA MSA</td>
<td>LA</td>
<td>0.0496971</td>
</tr>
<tr>
<td>Waterloo-Cedar Falls, IA MSA</td>
<td>IA</td>
<td>0.0495249</td>
</tr>
</tbody>
</table>

Fig. 8 Top 20 most congested MSAs, U.S. 2020
Comparison with Uber Data:

In order to supplement my research, I also used data sourced from the Uber Movement Initiative, which provided me with a larger dataset to analyze. Using datasets from San Francisco, Seattle, and Cincinnati, which were the only relevant datasets available for the U.S. that Uber had available, I created a dataset of approximately 64,000 observations, excluding those data points that were outliers in terms of speed. From this dataset, I created an initial chart (Fig. 8) outlining the change in average speeds throughout the month of March in 2020.

![Graph of average travel speeds throughout March 2020 using selected data collected from Uber Movement](image)

This data helps us further refine our conclusions, as it provides us insight into trips earlier in March before the pandemic was officially announced as a national emergency by then
President Trump on March 13th. One obvious trend we can see in this data is the increase in travel speeds right around the announcement of COVID as an emergency on the 13th. Speeds before the 13th tend to oscillate around 44 km/h, but after the 13th speeds quickly rise to an average of 50 km/h, which we hypothesize is due to the decreased congestion due to less travel from COVID lockdowns.

Because of the sampling methods used to create the Uber Movement datasets, the average speeds of trips that we see in the data tend to be different than the ones that we receive in our sample. This is because the dataset doesn’t measure actual travel speeds, but it averages the speeds of trips taken between different zones, which excludes the slowest parts of trips in general, which are the beginning and ending of each trip. However, we will attempt to use the Uber Movement dataset to compare changes in travel characteristics, without paying as much attention to specific values of relevant travel characteristics involved.

![Fig. 10 Conglomerated hourly speeds throughout March 2020 collected from Uber Movement datasets](image)
Next I examined the Uber data collected in March on an hourly level, which remains consistent with our previous charts that outlined speed changes throughout the day. We see a drop in speeds starting around 7am and staying low throughout the rest of the day, which seems to be mirrored by a similar dataset constructed from our original dataset as below in Fig 9. Although the range of speeds is much greater in Fig. 8 (with a difference of about 6 km/h in the first graph to a difference of about 3 km/h in the second) they show the same trends of speed changes throughout the day. Although the COVID pandemic lowered the number of people traveling, especially at the beginning, this shows us that hourly transportation patterns remained roughly the same from pre-pandemic to the pandemic era.
Above is data collected from the three available U.S. cities (San Francisco, Seattle, and Cincinnati) that had data for the three months in Q1 2020 (comprised of January, February, and March 2020), which helps us gain further insight into the effects of COVID on transportation in major U.S. urban areas. As we can see from the graph above, the data seems to show a drop in speed from January moving into February, with speed hovering around 49 km/h in January vs. lower average speeds of around 43 km/h in February. Right around March 13th, when COVID was announced as a national emergency, speeds started to rapidly increase back up to levels they were at earlier in the year before COVID-19 was a concern.
We don’t yet know how this trend continued past March into later pandemic months, but an initial reasonable hypothesis is that with some of the strictest lockdowns early on in COVID not showing drastic changes in data, later periods with less strict lockdown measures would probably also not show drastic changes from previous data, and would likely show speeds and characteristics closer to that of pre-COVID times.

Although we do not currently have data detailing transportation and trips past the month of March, this comparison is useful in that we can see that even during strict initial lockdowns, transportation speeds did not vary significantly from the previous months. This is mainly consistent with the initial theory that, although COVID may seem to strongly affect transportation, especially during heavy lockdown periods, the fundamental differences that create congestion in cities remain the same.
Conclusion:

Initial research into transportation patterns in the COVID pandemic era showed us a few things. First, COVID did change transportation characteristics, most importantly speed, generally increasing both speeds throughout the day in many sampled cities and increasing speeds from pre-COVID times. However, differences between cities did not see significant change, which signifies that the underlying factors that create the fundamental differences in congestion and transportation patterns within and between major urban centers has not changed.

Future research should most likely focus on the months after the pandemic was declared in the U.S. (starting with April 2020 and extending into the summer months), and attempt to perform further analysis to see what trends we can find after the initial reaction to the pandemic. Although the initial research shows us a few slight differences from pre-COVID times, more research may provide further insights into how transportation patterns changed over a longer period of time, and may help policymakers in the future better understand the impacts of policy on transportation modes and infrastructure in the U.S.
Bibliography:


