Measuring the Impact of COVID-19 Pandemic on Public Transit Demand in US

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1. Introduction

A novel coronavirus disease (COVID-19) has evolved into a global outbreak for its high contagiousness, high fatality rate, and lack of known treatments. To deal with the pandemic, Centers for Disease Control and Prevention (CDCs) and governments in different places recommended social distancing, self-quarantine, and work from home policies to stop the spread of the virus. However, the sudden shutdown also caused recessions in the domain of mobility, economic, and social activities. Different modes of transportation, especially mass transit, suffered considerable loss of passengers due to self-quarantine recommendation and contagion concerns. For example, as countries are closing their borders amidst the fear of transnational spread, the final week of March 2020 witnessed commercial flights dropped by 55% compared to the same date in 2019 (Weber 2020).

This sudden meltdown especially impacted the public transit system across the United States among other modes. It is natural and common to assume that sharing a narrow and unventilated space with numerous strangers is a bad idea during the pandemic. According to an online survey (sample of n = 1000 Americans and n = 1000 Canadians), about 48% of Americans and 40% of Canadians feel that riding transit poses a high health risk due to the virus (Yellin 2020). Even before the major outbreak, as the public become aware of the inevitable epidemic from the coverage of foreign and early domestic spread, the ridership begins to drop. For larger transit systems, for example, Washington Metropolitan Area Transit Authority reported that metrorail ridership has been reduced by 90% and bus ridership has been reduced by up to 75% by the end of March (WMATA 2020); for smaller transit system such as El Dorado transit in El Dorado county, California, the ridership also decreased by up to 75% (Christensen 2020). With the development of the pandemic and the decrease of transit demand, most transit authorities in different states began to adjust their service schedules accordingly (Sound Transit 2020; UTA 2020).

As the recessions continue to grow, we still cannot have a grasp of its extent, geographic and temporal variation, and its relevance with the development of pandemic. One major reason is that most transit systems will not or have yet to release their ridership data, and it will take a long time to collect these data for each system. In this paper, we use the transit demand decrease data obtained from the Transit app to infer the change of ridership. We use logistic model to fit the data of each transit system and get the key parameters from the models: background value, which represents the degree of social distancing; decay rate and half-life, which represents the speed of the recession; 5 percentile value, which represents the initial date when the transit demand began to decrease. We also calculate the distance between the transit demand decrease curve and the disease cases number curve. The results: ----------------

1. Background

Although it may be the first time for the last 30 years that the US society witnesses a total lockdown at the nationwide scale due to a pandemic, there are still sources and experiences about how a pandemic can impact the transit system in different contexts.

1. Analysis

In this section, we first introduce our data sources of the transit demand and COVID-19 daily cases statistics. Then, we introduce our theory about the dynamics of transit demand and three key parameters in the model. Then, we investigate the linkage between the transit demand curve and case increase curve.

* 1. **Data sources**

**Transit demand change.** We collected the transit demand change data via the web interface maintained by Transit app. Transit is a popular mobile app providing real-time public transit data and trip planning. The app covers over 200 metropolitan areas around the world with more than 5 million download on Android platform (Transit app 2020b). Therefore, although the actual ridership data is still largely unknown and inaccessible, the usage of the app can be regarded as a rough measure for the transit demand of these app users (Transit app 2020a). Surely, the difference between the behaviors of apps users and other users, the accurate ratio of apps users among all transit users, and other factors affecting the representativeness of the usage statistics are still largely unknown. However, we can still use it as a rough but reasonable proxy to capture the changes of transit demand and ridership caused by the COVID-19 pandemic due to the large user group and popularity of real-time transit apps.

As COVID-19 hit the world and the transit demand decreased consequently, the app website kept updating on the changes of transit demand on an everyday basis. The change values are a set of percentage, calculated by comparing actual usage of the app to projected use of the app based on last year’s numbers. The projected numbers are also adjusted for annual growth (Transit app 2020a). In this way, the values represent the difference between expected and the actual transit demand.

The data includes 182 public transit systems across the United States, Canada, Australia, New Zealand, and France. We select all 121 transit systems in 71 metro areas, 55 counties, and 30 states across the United States and conduct analyses based on these areas.

**COVID-19 case numbers.** We collected the daily case numbers from the COVID-19 Surveillance Dashboard produced by University of Virginia (Biocomplexity Institute 2020). The data includes all counties in the US for every day. To find the linkage between the case numbers and the demand decrease, we geocoded each transit system to the corresponding county or multiple counties if cross-counties systems.

**Google search trend.**  Amidst the pandemic, one of the most important factors is people’s awareness. Searching on the search engine, such as Google.com, has become the most common practice for people to acquire knowledge and information nowadays. Meanwhile, unlike other social media platforms such as YouTube or Twitter, Google search engine does not have a recommendation system, which means users will only search actively. Therefore, the frequency of searching on the Google search engine is a very good indicator. We will collect the Google search trend data for different sub-region across the United States.

* 1. **Logistic model for daily transit demand change**

We first plot the scatter point graph for all systems together as shown in Figure 1. For all systems at the start, the demand generally oscillate around the base line. As the epidemic and quarantines progressed, the demand gradually decreased, until reached a very low level and then stabilized.

Figure 1: the scatter point of all systems' daily demand change.

The shape of the curves can be easily connected with logistic function; therefore, to generalize the change of transit demand, we will use logistic function to fit the data. A logistic or sigmoid function can be expressed into the following form:

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| --- | --- | --- |
|  |  | (1) |

Where: is the curves’ minimum decreased value, is the curves’ baseline value, k is the logistic growth rate or steepness of the curve; t represent the time (day) and is the day when the function reaches the midpoint. We will fit each transit system’s demand data using logistic model individually and calculate these three parameters. In the next section, we discussed the trend of three parameters for each system.

**Background value.** In the logistic model, the parameter B represents the range of the logistic curve. The curve will decrease rapidly and then stabilize around the B value, therefore we name it *background value.* In the practical sense, it represents the ratio of public transit users in this system that still will not or cannot stop using it regardless of the pandemic. For different systems in different metro areas, the background value is vastly different due to their different social and economic status.



Figure 2: The distribution of background value across the United States.

The first factor that can have a significant impact on the background value is the non-physical occupation composition; or more specifically, the ratio of population that can work from home. If an area has higher ratio of non-physical jobs, workers can easily work from home thus the transit demand will decrease further.

The second factor is the dependency on transit, which can be measured with the ratio of public transit to work or transit commuter rate. Supposing two areas with same non-physical jobs ratio, the area with higher transit commuter rate can witness less demand decrease since more people still rely on the transit system to commute.

The third factor is the awareness, which can be measured by the Google search trend data and the date of declaring state of emergency by local government and self-quarantine order by local CDC and the Google Search trend data.

The regression analysis shows that:

**Divergent point and convergent point.**

As we visualize the curve of the transit demand, the decrease mainly happens during a relatively short period in the middle. Therefore, to measure when the demand start to decrease and finally finish the decreasing process, we introduce two measures: divergent point and convergent point . We apply the confidence interval theory to the definition of the measures by first construct the probability density function of the normalized logistic function F(x):

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| --- | --- | --- |
|  |  | (2) |
|  | Then: , and | (3) |

Where: P is the probability density function of the normalized logistic function; to normalize the logistic function, we subtract the baseline and divide the result by B to construct the P function so that . is the confidence level. We choose 5% for the confidence level, which is a widely accepted value. The significant level is a useful threshold to decide whether a fitted value changes significantly compared to the baseline value/background value.

From the formula (3), we can induct that , which means under the confidence level of 0.95, we can make sure most change happen between the divergent point and convergent point. From the formula, we give the direct definition of divergent and convergent point:

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| --- | --- | --- |
|  | and | (4) |

Moreover, the two measures are not directly calculated from the raw observed data, instead, we obtained the measures from the smoothened curve to remove the stochastic noise. They can be a stable indicator to measure the start and end of the demand decrease.

Beyond its statistical meaning, divergent point represents the first daywhen the demand curve began to diverge from the normality. It also represents when the transit users start to realize they should avoid the transit trips. Convergent point, on the other hands, represents when the decrease finally finishes. After the convergent point, the transit demand will persist at a stable level. In the next section, we will compare the two measures with the development curve of the pandemic cases.

**Decay rate.** Beside the divergent point, the speed of recession is another aspect. The parameter represents the curve’s decreasing speed from the baseline value to the background value. Therefore, we name it *decay rate*. Decay rate can be an important indicator for the actual response speed of urban residents/public transit users to the pandemic. Figure 3 shows the distribution of the decay rate.

Although the decay rate works well, the rate value per se does not have any physical meaning. Instead, we would like to use a temporal indicator to represent the speed and duration of the decline. From the logistic model, represents the time/days from the day zero to the curve reaches the midpoint of the curve. It reflects two major temporal factors for the pandemic: the initial date of epidemic outbreak, which is measured by the divergent point, and the half-duration of decay. Therefore, we introduce half-life:

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| --- | --- | --- |
|  |  | (4) |

Half-life is only determined by the decay rate. Half-life indicates the duration of the duration of the demand decrease.

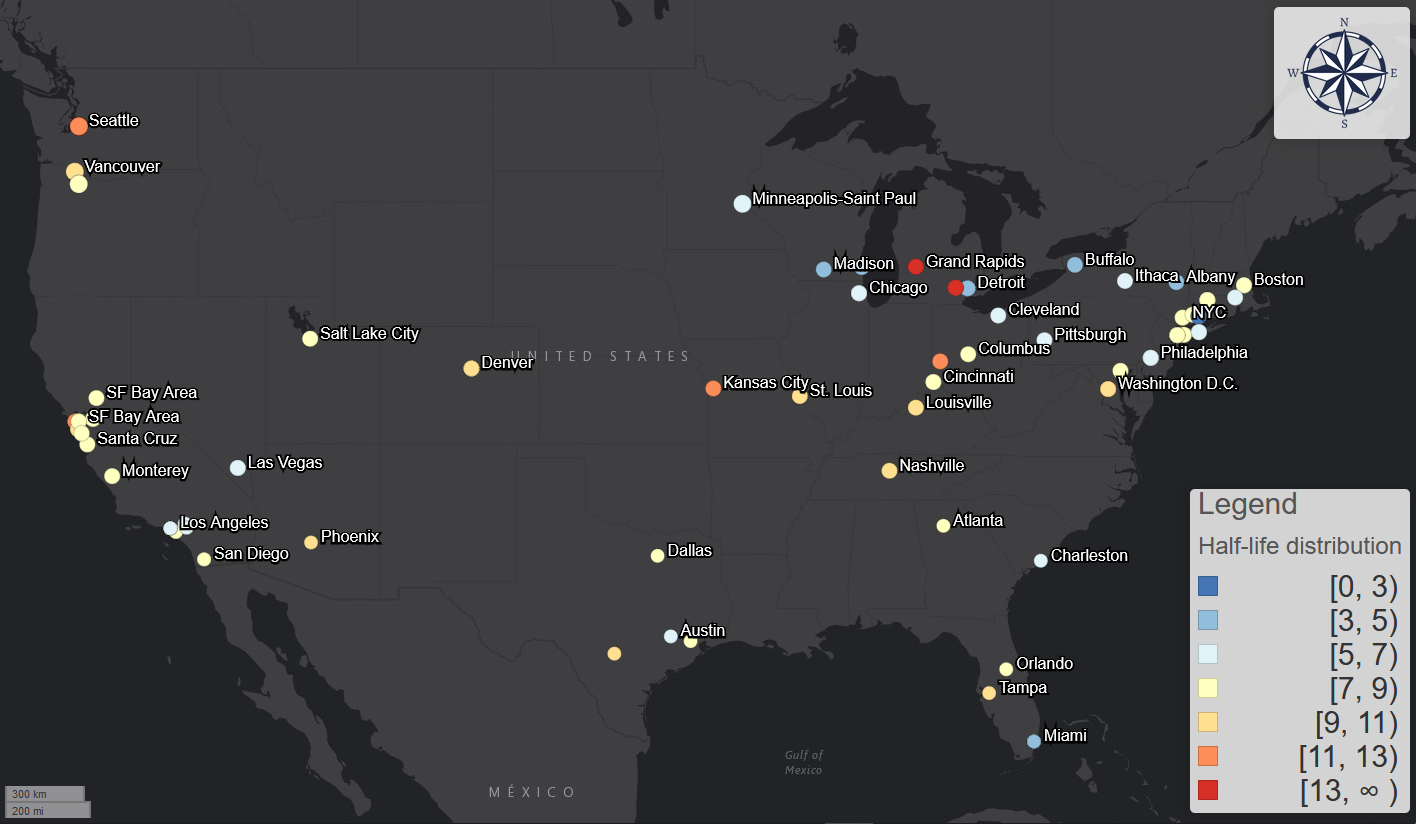


Figure 3: the distribution of half-life

* 1. **Desynchronization between demand decrease and epidemic.**

The process of transit demand decrease is not synchronous with the development of the pandemic. To measure the difference between the two curves, we can compare the divergent point when transit demand decreased and the first day when the pandemic is first confirmed to begin to spread in the local community. This measure also indicates the transit users’ responses compared to the actual development of the pandemic. If the value is smaller than 0, it means most transit users are still using the transit systems as their usual routine; if the value is bigger than 0, it means the transit user community started to make a response, regardless of the speed (decay rate) and the extent (background value) of the response, prior to the confirmation of the local outbreak. Another similar metric is the difference between the date of first confirmed case and the convergent point, which shows whether the user can totally avoid the transit trips when the actual epidemic arrives.

However, there is another necessary factor that should be taken into consideration beyond the date of first confirmed. The median of incubation period is 5 days and can be as long as 14 days (Lauer et al. 2020). Meanwhile, numerous studies have proven that the virus can spread asymptomatically (Cheng et al. 2020; Dong et al. 2020; Pan et al. 2020). Therefore, the actual initial date when the virus began to spread in the local community can be traced back to 4 - 14 days ago. This lag can be even longer considering the lack of testing kits and slow response for the local authority (Achenbach et al. 2020; Popovich 2020). Therefore, it is necessary to consider this temporal lag ahead of the first confirmed date. Therefore, we can introduce an *incubation lag* parameter in the measures; it measures the temporal delay factors beyond the first case confirmed, such as incubation period and testing delay. Here, we introduce the definition of *response interval* from divergent point and convergent point:

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|  |  | (5) |

Where: is the date of first confirmed case in the county of the transit system; l is the incubation lag; and are the divergent and convergent point. Positive response interval means that the transit users responded earlier than the epidemic spread; the larger the value is, the less risk the transit users are exposed to the virus. For the two versions, the divergent version focuses on the transit users’ awareness while the convergent version focuses on both the awareness and the response speed. Next section we are going to discuss them separately.

Figure 4 shows the distribution of the response interval measures in the US from both divergent and convergent point for incubation lag = 0, 5, 14 days. Figure 5 shows the impact of incubation lag on the ratio of transit systems with positive response intervals (earlier response).

For response intervals from the divergent point: when not considering the incubation lag, the pattern is highly polarized. In some cities with international airports, such as Seattle, Washington State where the first US COVID-19 cases were found, people still used the transit even after the first case emerges. Meanwhile in other cities, such as most cities in Middle West except Chicago, although the cases have not been found in these cities, people already started to avoid transit trips. This can be because the media began to report the severity of this disease and CDC made the prediction that the community spread is inevitable near the end of February 2020 (McLauphlin 2020).

However, after we consider the incubation lag = 5 days, which is the reported average incubation period, many areas with earlier response now have negative response interval. A most noticeable area is the New York City. With lag = 0, out of 13 transit system in the New York City, there are 5 systems that have positive response intervals, such as MTA - Bronx buses, Suffolk County Transit, and Long Island Rail Road; when lag = 5, all of the 13 transit systems all have negative response intervals. This also suggests that New York transit users did not realize the necessity of avoid transit and non-essential trips when the community spread began. On the contrary, most transit systems in the Middle West such as Missouri, Ohio, Michigan, and Kentucky still have positive response intervals. This phenomenon is also supported by the cellphone location data: those places mentioned above had known stay-at-home orders before March 27th and the measured trips are significantly less (Glanz et al. 2020). Due to earlier response, the transit users in these area may be exposed to less risk during the pandemic.



Figure 4: the geographic pattern of response interval with incubation lag = 0, 5, and 14 days for both from divergent and convergent point.

For the scenario of lag = 14 days, which is a highly hypothesis scenario, most transit systems and most cities have negative response. Ohio is the one of the relatively earliest responding states.

However, the situation is not going well for the response intervals from convergent point, which represent how earlier is each transit system’s users finished the stay-at-home process. For scenario of lag = 0, only Capital Metro in Austin, Texas and HRT in Hampton, Virginia. For the case of Austin, the city and county authority declared the local state of emergency in March 6th (Evans 2020), which is one of the earliest places to take actions in the South, even in the United States. This can be one reason for the relatively fast and earlier reaction of transit users. For larger lag such as lag = 5 and 14 days, no transit systems and cities have positive response intervals.

Figure 5: Trend of the ratio of transit system with positive response interval for different incubation lag

* 1. Hourly pattern.

TBD.

Need the raw data, or at least the ridership of each day.