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Executive orders or public fear: What caused transit ridership to drop in Chicago during COVID-19?
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A R T I C L E   I N F O
Keywords:
COVID-19
Transit ridership
Bayesian structural time series
Dynamics model
Telecommute
Remote work
Regression analysis
Ridership recovery
Mobility

A B S T R A C T
The COVID-19 pandemic has induced significant transit ridership losses worldwide. This paper conducts a quantitative analysis to reveal contributing factors to such losses, using data from the Chicago Transit Authority’s bus and rail systems before and after the COVID-19 outbreak. It builds a sequential statistical modeling framework that integrates a Bayesian structural time-series model, a dynamics model, and a series of linear regression models, to fit the ridership loss with pandemic evolution and regulatory events, and to quantify how the impacts of those factors depend on socio-demographic characteristics. Results reveal that, for both bus and rail, remote learning/working answers for the majority of ridership loss, and their impacts depend highly on socio-demographic characteristics. Findings from this study cast insights into future evolution of transit ridership as well as recovery campaigns in the post-pandemic era.

1. Introduction

The COVID-19 pandemic has had far-reaching impacts on public health, the economy, and ways of living. In particular, various regulatory strategies (e.g., remote study/work and stay-at-home executive orders, mask mandates for indoor activities, social distancing, and sanitation protocols for public services), along with people’s perceived risk of infection from shared vehicles, have altered people’s travel needs and mode choice behaviors. This, in turn, has led to significant and prevailing public transit ridership reductions. Transit agencies, as well as the general public, face the pressing need to better understand the factors that may have contributed to transit ridership loss, and the extent of their impacts. Such understandings are important because they are critical for transit systems to anticipate demand and to plan services in the long run.

In this study, we use data from the Chicago Transit Authority’s bus and rail systems to quantify the impacts of public fear and regulatory orders on the prevalent transit ridership losses. Specifically, we address the following key questions: (i) What are the primary factors that have contributed to the current transit ridership loss under COVID-19? (ii) How do the effects of these factors vary over time (e.g., development stage of the pandemic), space (e.g., city neighborhoods), and transit modes (e.g., rail and bus)? (iii) How could transit ridership recover, if at all, to pre-pandemic levels? And (iv) how can the transit agencies learn from the current ridership variations to enhance decision making (e.g., to stimulate ridership and to plan service) in the future?

The transportation industry is very concerned about the COVID-19 pandemic because it has already thoroughly altered people’s travel behaviors and disrupted the demand for all modes of transportation services worldwide. The evidence is abundant for not only public transit, but also personal vehicles and bike-sharing systems (Teixeira and Lopes, 2020; Parr et al., 2020; Padmanabhan et al., 2021; Bliss et al., 2020; Wang and Noland, 2021). More specifically, major U.S. cities have suffered sharp decreases in transit ridership ranging from 65% to 90% reduction within the pandemic’s first few months (Gao et al., 2020; Wilbur et al., 2020).
Besides ridership decreases, studies have consistently shown that ridership losses vary among different spatial neighborhoods as well as different socio-demographic groups. A common conclusion is that lower-income people, less-educated people, and minority groups experienced the largest behavioral changes in the U.S. (Bliss et al., 2020; Brough et al., 2021; Garza, 2020; Sy et al., 2020; Transit, 2020; Wilbur et al., 2020; Hu and Chen, 2021; Tirachini and Cats, 2020; Liu et al., 2020; McLaren, 2020; Fissinger, 2020), mainly because their jobs are more likely to be “in-person” as parts of the society’s “essential” functions, and therefore they have to continue working through the pandemic due to lack of flexibility and choices (Kantamneni, 2020). Nonetheless, it shall be noted that such observations are highly dependent on the socioeconomic characteristics of the community, and this is particularly the case if we look at other countries in the world. For example, recent studies outside of the U.S., such as those in Australia and Turkey, have shown that lower income groups have also reduced their travel significantly, to an extent such that the disparity among different socioeconomic groups largely obscure in those countries (Beck and Hensher, 2020; Shakibaei et al., 2021).

Many factors may have contributed to the sharp ridership loss. Intuitively, mandatory stay-at-home orders, quarantine orders and social distancing requirements should have a direct and significant impact. Yet, the ridership numbers seem to be prevailing low even in cities and states that were the first to be labeled as “reopened” (The New York Times, 2020; Apple, 2020). This suggests that the stay-at-home and quarantine orders may not be the only factor that has influenced transit ridership. Instead, evidences from past pandemics (and early stages of the current pandemic) suggest that the level of public fear and risk perception towards enclosed public spaces (e.g., transit vehicles) could play a role in discouraging the passengers from using public transportation (Wang, 2014; Sung, 2016; Parker et al., 2021; Cho and Park, 2021). People’s perception of risk during a pandemic could be based on objective risk measures (Wang, 2014) (e.g., daily confirmed cases and daily deaths), as well as subjective risk measures and media attention (Fenichel et al., 2013; Von Winterfelt and Prager, 2010). It was found from past epidemics and pandemics (such as SARS, H1N1, and MERS) that the effects of public fear and risk perception on transit ridership normally lingered for a few months beyond the end of the pandemic or epidemic (Liu et al., 2022).

Compared to those previous pandemics, however, the COVID-19 pandemic has lasted much longer and has been spreading far more widely. In addition, the presence of new social media and communication technologies, as well as the rapid growth of the e-commerce industry, has contributed to its unique socioeconomic background. For example, many industries and schools have widely used remote access technologies during this pandemic to prevent the COVID-19 virus from spreading at work places, which has not only changed the ways of living, but also caused public transit demand to plummet. Government-mandated stay-at-home orders worldwide have forced the closure of public recreational facilities (e.g., gyms, parks and trails), discouraged people from traveling for other purposes (e.g., social gatherings and group sports), and in turn depressed transit demand from almost every sector of the population. It is therefore an open question whether the significant transit ridership drop due to COVID-19 will last a much longer time (if not forever).

It is critical for public agencies to understand the expected magnitude and duration of transit ridership drops during a pandemic (such as COVID-19), as well as to quantify the extent to which psychological and socioeconomic factors contribute to such transit ridership changes. In particular, it is important to estimate how much of the observed ridership loss can be attributed to pandemic-related factors, such as remote work, quarantine orders, fear of infection, or risk perception, and how these factors may have imposed long- or short-term impacts on the passengers’ travel behaviors. Only in this way can agencies properly plan and allocate transit service resources in accordance to future pandemic developments, such as an spike of COVID-19 mortality, new government mandates, or even the termination of the pandemic.

The main objective of this study, therefore, is to enrich our understanding of transit ridership’s temporal variations and spatial disparities that have been observed so far, so as to inform policy decision making in the future. In so doing, this paper develops a sequential statistical modeling framework to quantify the impacts of various contributing factors (e.g., government executive orders, public fear and crowd avoidance behaviors) on spatiotemporal changes of the transit ridership. In the temporal dimension, we first implement a Bayesian Structural Time Series (BSTS), similar to the one used in Hu and Chen (2021), to estimate the counterfactual ridership during the pandemic for the entire first year of the pandemic. Then, we fit the daily ridership loss with a new dynamics model which explicitly addresses the various factors (e.g., presence of government executive orders, and instant and residual fear for the pandemic) while fitting the counterfactual ridership to the observed ridership. In the spatial dimension, we perform a set of linear regression analyses to connect the socioeconomic and land use characteristics of spatial neighborhoods to the dynamics model estimates. Results from the case study on CTA bus and metro systems show that the public fear affects modes differently and that the majority of the ridership loss is due to regulatory factors rather than voluntary self-protection behavior — this implies that the ridership will likely bounce back by a significant amount shortly after the government executive orders are lifted, followed by a small amount as remaining public fear gradually dissipates after the pandemic is over. Results also show how the ridership robustness level differs across bus and rail modes against the pandemic. The insights from this study can be used by transit agencies as the basis for predicting future ridership, planning ridership recovery campaigns, and designing service routes and schedules during and after pandemics.

The rest of the paper is organized as follows. Section 2 provides a literature review of relevant studies that have investigated the public transit ridership during not only the COVID-19 pandemic but also previous epidemics and pandemics. Section 3 describes data collection, processing, and preliminary data analysis. Next, Section 4 presents the proposed statistical modeling framework. Section 5 presents model results and major findings. Finally, Section 6 provides concluding remarks and discussion.
2. Literature review

Before COVID-19, studies had found evidence on the relationship between “public fear” (e.g., measured by the number of infection cases) and transit ridership variations during past pandemics. For example, Wang (2014) built a dynamics model to relate the daily metro ridership in Taipei City to the daily reported cases of the Severe Acute Respiratory Syndrome (SARS) in 2003. The study found that each newly reported SARS case resulted in an immediate loss of about 1200 metro rides, and it had a lasting effect or “residual” fear of 28 days. Sung (2016) studied how the fear from the outbreak and spread of the Middle East Respiratory Syndrome (MERS) in Korea during the year of 2015 affected the number of public transit users. The study found that the ridership did not immediately drop but instead had a delayed effect as the infection cases increased. Furthermore, the magnitude and frequency of notable ridership drops was dependent on the trip purpose. More consistent morning commute trips were affected much later and in lesser magnitudes, while evening hour trips (often for leisure) were affected immediately and with greater magnitudes. Nonetheless, the data showed that the reduction in trips for both morning and evening rush hours was not permanent, and the ridership recovered to the normal level after a period of about 6 months (Sung, 2016). Moreover, Fenichel et al. (2013) investigated air passengers’ voluntary defensive behaviors during the H1N1 pandemic in the United States. They used air passenger records from US Airways to show the number of missed flight reservations during the H1N1 pandemic. They used Google Trends data (i.e., Internet search frequency) on “swine flu” and “H1N1” to show public perceptions of H1N1-related risks, as well as reported H1N1 cases from the WHO’s FluNet database to represent the H1N1 pandemic’s actual risks. The results indicated that 0.34% of missed flights can be attributed to passengers’ defensive actions, and that people were more sensitive to pandemic-related media coverage than objective risk measurements (such as the number of reported cases). These findings emphasize the importance for agencies or authorities to convey clear information to the public — proper information sharing and transparency help people avoid irrational behaviors induced by their fear, and in turn, help societies avoid excessive costs during pandemics. Another study, Ives et al. (2009), focused on the behavioral changes of the health workers during the H1N1 pandemic. This study split the volunteers into nine focus groups (for participant-led discussions) and five interview groups (for those not available to join the discussions) on a series of healthcare-related topics. It observed that health workers were discouraged from working during H1N1 by various factors, such as infections of the disease, inconvenient transportation, family responsibilities, and lack of trust in the healthcare systems. In particular, some health workers expressed concerns about the risk of infection during commute with public transit.

During the COVID-19 pandemic, a vastly growing body of literature has also observed changes in travel behavior which are not only due to executive stay-at-home orders but also due to an increase of public fear and crowd avoidance. Rauws and van Lierop (2020) studied factors that may have been affecting transit customers’ loyalty in Utrecht, Netherlands. The study surveyed 829 participants and found that the odds of frequent transit users to use public transit were 41% lower when they experienced fear of infection. A similar result was also observed of other transit user (i.e., including infrequent users). The study concluded that before the pandemic, travel satisfaction was one of the most important factors for customers’ loyalty, while during 2020 and 2021, the loyalty is expected to be determined by fear of infection, option to work from home, and mode availability. This finding is consistent with those observed in the United States. Parker et al. (2021) examined individual travel behavior changes by analyzing both smartphone-based travel data and panel survey responses administered in August of 2020 to a representative sample of the United States population. Respondents listed factors such as sanitation, widespread use of face mask, vaccine deployment, COVID-19 infection rates, and reduced crowding as the top factors that might encourage their return to transit. Crowd avoidance has been shown to increase during the pandemic and become a significant factor for people’s transit use. Cho and Park (2021) compared the passenger’s crowd avoidance behavior through two surveys, one conducted in October of 2018, and the other in November of 2020, in the Seoul metropolitan area of Korea. The results, based on a random-parameter mixed logit model, suggested that crowding impedance (measured by willingness to pay) after COVID-19 outbreak are up to 1.23 times higher than before, and notably, subway passengers were more concerned about crowding than bus passengers.

Interestingly, this difference in risk perception across modes has been observed by other studies as well. Shamshiripour et al. (2020) designed a travel behavior survey distributed in the Chicago Metropolitan Area from April to August of 2020. Besides questions related to socio-demographics, health, and daily activity, the study asked participants about the risk perception of various modes of transportation. The results showed that people perceived personal vehicles having the lowest risk, followed by riding private bicycles and walking. In contrast, the greatest risk was perceived to be associated with transit, taxi, and ride-hailing — 93% of the respondents identified transit as a medium to extremely high risk mode for COVID-19 exposure. This is in agreement with other studies on bikesharing and transit ridership during the pandemic (Wang and Noland, 2021; Teixeira and Lopes, 2020; Hu and Chen, 2021; Padmanabhan et al., 2021). Teixeira and Lopes (2020) studied the resilience of bike sharing systems as compared to the subway in New York by comparing their ridership shortly after the executive orders in March 2020. While both modes experienced a significant drop in ridership, the bikesharing system proved to be more resilient by having a less significant ridership drop, and there might have been a possible modal shift from transit to bikesharing. Later, Wang and Noland (2021) extended this analysis and found further evidence of bikesharing resiliency — by September of 2020, the bikesharing ridership had recovered to the 2019 level, but the subway ridership was still in a 30% deficit. Hu et al. (2021) also came to the same conclusion after comparing bikesharing with transit, driving, and walking in the city of Chicago. Overall, during the pandemic, the bikesharing system seems to have shifted from being a complement to being a substitute of transit.

Publicly available multimodal data have been used to quantify ridership changes in different transit modes under COVID-19. Hu and Chen (2021) studied ridership decline on the “L” rail system in Chicago for the first 1.5 months of the pandemic (until April 30, 2020). They used a Bayesian structural time-series (BSTS) model to produce the counterfactual ridership numbers, and a partial least square (PLS) regression model to evaluate socio-demographic factors and land-use characteristics that may explain this decline. In
agreement with studies performed around the United States (Brough et al., 2021; Sy et al., 2020; Wilbur et al., 2020; Liu et al., 2020), researches found that socio-demographic characteristics, level of education, and household incomes are significantly correlated with transit ridership during the pandemic. Fissinger (2020) studied the travel behavior among Chicago travelers before and during the COVID-19 pandemic. This study used daily account-based data from Ventra fare payment system (Ventra, 2021) to study the trips of each individual traveler (as opposed to aggregated ridership numbers). It was found that ridership change to be highly heterogeneous among two identified groups of riders: (i) “high range frequent peak rail riders”, primarily higher-income, and mostly Caucasian, individuals from northern Chicago; and (ii) “high range frequent off-peak bus riders”, mostly from the south side of Chicago. The trip decline was 80% for the former group, but only 33% for the latter group. Spatial regression analysis also showed that the proportion of users holding transit passes were associated with higher ridership during the COVID-19 pandemic, most likely due to these users’ transit dependence. This study also found a significant racial disparity, showing that the proportions of black and Spanish-speaking residents are strong predictors of low ridership drops.

Last but not the least, many media reports have highlighted observations that people have become less vigilant about the virus and about following the Centers for Disease Control and Prevention’s guidelines as the COVID-19 pandemic drags on, a phenomenon known as the “caution fatigue” (Brazell, 2020; Dozois, 2020). Psychological studies also indicate that recurrent and continuous exposure to fear, especially when people are adjusting their expectations to outcomes, can lead to reduction or even extinction of fear (Davis et al., 2006; Hofmann, 2008). The COVID-19 pandemic has lasted about 18 months in the United States (so far, at the writing of this paper) and the case infection fatality rate (i.e., cumulative deaths divided by cumulative cases) in the United States has continuously decreased since the end of May 2020 (The New York Times, 2021). Given the declining risk perception and the pandemic’s long duration, “caution fatigue” of COVID-19 is inevitable and could significantly impact people’s transit riding behavior. This shall be addressed.

3. Data analysis and processing

To analyze transit ridership patterns over time and space, we selected the Chicago Transit Authority’s (CTA) bus and rail systems. The CTA serves as a good testbed because they intentionally kept their service frequency and coverage during the pandemic (DeWeese et al., 2020). As a result, the ridership reduction caused by transit service adjustments is negligible, and hence the major reasons behind ridership fluctuation could be attributed to people’s fear for the pandemic, as well as policy changes and executive orders.

The ridership data for both the CTA rail system and CTA bus system are extracted from the Chicago Data Portal (City of Chicago, 2021b). The CTA rail ridership data are provided by the entrance stations, while the CTA bus ridership data are collected as daily boardings per bus line. Fig. 1 presents the Chicago Transit Authority’s (CTA) total daily bus and rail ridership from March 1, 2020 to March 1, 2021, along with daily reported deaths. We see that both rail and bus ridership suffered a sharp drop on March 16, 2020 (i.e., the start of quarantine orders), falling to approximately 20%–25% of the pre-COVID-19 ridership levels. After that, the ridership for both modes seemed to slowly bounce back until July, after which it stabilized at about 30% of the pre-COVID-19 ridership numbers until the end of October. In November, ridership started to decline again when the reported deaths rose again, and finally, gradually built back up again. The same trend can be observed from data of other transportation services in Chicago such as ride-sharing services, commuting rail, and suburban buses (Fissinger, 2020; Tyler, 2021; Regional Transportation Authority Mapping and Statistics, 2021).

As both the COVID-19 outbreak in Chicago and notable transit ridership reduction started in late March 2020, the pandemic period in this study is set to start on March 15, 2020 and last through February 28, 2021 (limited by ridership data availability). By combining the findings from literature and observations from current pandemic as shown in Fig. 1, the possible factors contributing to the ridership dynamic fluctuations include the pandemic objective measures (e.g., daily reported deaths), media attention (e.g., Google queries), policies (e.g., remote working/learning), and executive orders (e.g., school shutdown and stay-at-home orders). The daily COVID-19 deaths in the City of Chicago are obtained from The New York Times (The New York Times, 2021). The media attention on the COVID-19 pandemic is represented by the daily normalized Google Trends data, which give a daily score of the proportion of searches on a particular topic over all searches in a particular place and time (Rogers, 2016). We extract the Google Trends data of the keyword “coronavirus” for the study period using the technique presented in Dyachenko (2021); see Fig. 2 for the illustration of the obtained Google Trend data. Furthermore, the detailed information about stay-at-home orders is obtained from the City of Chicago’s website (City of Chicago, 2021a). According to the website, one stay-at-home order officially took place from March 26, 2020 to June 3, 2020, and the other from November 16, 2020 to January 22, 2021. We do not have detailed data for the dates and duration of remote working mandates in each industry and those of remote learning in different schools/universities. Therefore, we assume that these events came into effect on March 17, 2020, when the Governor of Illinois issued school closure executive orders (State of Illinois, 2021). We further assume that these events were continuously enforced throughout the study period.

In addition, we observe that the Google Trend scores have a general decreasing trend. It may indicate that people’s fear or cautions toward COVID-19 virus may decrease as the pandemic drags on, and therefore, the “caution fatigue” phenomenon (Brazell, 2020; Dozois, 2020) is considered as a factor in this study. This aligns with the observation that the transit ridership was less affected during the second peak of COVID-19 deaths than that during the first peak from Fig. 1.

Our preliminary data analysis further shows qualitatively that the relationships between the rail and bus ridership reductions and the socio-demographic characteristics are very prevalent. For instance, Fig. 3 overlaps the proportion of African American population...
in each of the census tract areas and the percentage change in ridership in those neighborhoods. In Fig. 3(a), the rail stations most affected by the pandemic (i.e., those with ridership percentage loss greater than 72.8%), represented by solid squares, are located mostly in downtown and northern Chicago; those neighborhoods also have lower proportions of African American population. A similar north-vs.-south split is also observed in the bus lines, as the dotted lines, which bear greater decreases in ridership, are mostly located in northern Chicago; see Fig. 3(b). Similar spatial correlations have been observed for other characteristics such as income. Fig. 4 presents the same ridership data for both modes, which are now overlapped with the average annual per-capita income in each area. The north–south split still exists which seems to also agree with the ridership reduction pattern. Other socio-demographic variables, such as the proportion of population under the poverty line, and the level of education, exhibit similar relationships.

\footnote{Here, the percent change in ridership is calculated based on (i) the total ridership from March to December, averaged across 2017–2019, and (ii) the total ridership over the same months in 2020. Then, the Jenks natural breaks classification method is applied to split the rail stations and bus lines into two major groups.}
In light of these observations, this study also collects data on a vast number of socioeconomic characteristics that could be related to ridership spatial disparities. These data types are presented in Table 1. Data on socio-demographic characteristics are available at the US Census Bureau (US Census Bureau, 2020) with different spatial resolutions: demographic data are extracted by census tracts and origin–destination employment information can be found for census neighborhood blocks. Parcel-based land use data can be found from the Chicago Metropolitan Agency for Planning’s land use inventory (Chicago Metropolitan Agency for Planning, 2015). The entropy-based land use mix index (LUM) is used to measure the degree of mixed land use, with $LUM = 0$ being homogeneous, while $LUM = 1$ being maximum mixture (i.e., equal area split for every land use type) (Cervero and Kockelman, 1997). It is calculated as follows:

$$LUM = \begin{cases} \frac{-1}{\log N} \sum_{i=1}^{N} p_i \log p_i, & N > 1 \\ 0, & N = 1 \end{cases}$$

(1)

where $N$ is the number of land-use types in an area, and $p_i$ is the percentage of land type $i$ within this area.

Finally, in order to simultaneously consider the temporal and spatial variations, we assume that riders generally would approach the closest rail station or bus stop from their origin. Therefore, we analyze the socio-demographic characteristics of the regions around the rail stations or bus routes via appropriate geographic data matching process. For the station-level rail ridership data, we first determine the catchment area of each rail station via a Voronoi tessellation. For the outer-most stations, a maximum range of five miles is set to avoid unrealistic catchment area sizes. The result is shown in Fig. 5(a). We then obtain the intersection between the geographic area of each socio-demographic spatial unit and the station catchment area, and use the population of the intersected regions as weights to aggregate demographic data. The land use data are aggregated to each station by using the intersected area size (instead of the population) as the weight. For bus system, each bus line may intersect with several census tracts, so we aggregate

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2 We consider both the proportion of residents (living in a catchment area) and the proportion of workers (working in a catchment area) in the analysis because, intuitively, the former could provide information about the boarding counts for morning commute trips and leisure trips, while the latter may mainly provide insights on the evening commute.

3 The 5-mile radius is also set along the perimeter of the city to account for larger catchment areas that may result from the CTA’s park-and-ride facilities along the peripheral stations.
Table 1

| Variable            | Description                                                                 |
|---------------------|-----------------------------------------------------------------------------|
| prop.age_0_24       | Proportion of population between 0 and 24 years old                         |
| prop.age_25_39      | Proportion of population between 25 and 39 years old                       |
| prop.age_40_64      | Proportion of population between 40 and 64 years old                       |
| prop.white          | Proportion of white population                                             |
| prop.black          | Proportion of black population                                             |
| prop.asian          | Proportion of Asian population                                             |
| prop.edu            | Proportion of population with at least a high school degree                |
| prop.employ         | Proportion of population employed                                           |
| prop.poverty        | Proportion of population under the poverty line                            |
| prop_R_manuf        | Proportion of residents with jobs in the manufacturing industry            |
| prop_R_trade        | Proportion of residents with jobs in the wholesale or retail trade industry|
| prop_R_edu          | Proportion of residents with jobs in the educational service industry      |
| prop_R_health       | Proportion of residents with jobs in the health industry                   |
| prop_W_manuf        | Proportion of workers with jobs in the manufacturing industry              |
| prop_W_trade        | Proportion of workers with jobs in the wholesale or retail trade industry  |
| prop_W_edu          | Proportion of workers with jobs in the educational service industry        |
| prop_W_health       | Proportion of workers with jobs in the health industry                     |
| prop_LU_residential | Proportion of residential land                                             |
| prop_LU_commercial  | Proportion of commercial land                                              |
| prop_LU_industrial  | Proportion of industrial land                                              |
| prop_LU_education   | Proportion of educational institutional land                               |
| prop_LU_medical     | Proportion of medical institutional land                                   |
| prop_LU_transportation | Proportion of land used for transportation purposes                      |
| prop_LU_openspace   | Proportion of open space land                                              |
| LUM                 | Entropy-based land use mix index                                           |

(a) CTA rail stations. (b) CTA bus lines.

Fig. 4. The average annual per-capita income and the percentage change in total ridership by mode.
all socio-demographic information at the census tract level, and use the number of bus stops within each census tract as the weight to obtain the average socio-demographic characteristics along this entire bus line.4

During this process, those rail stations and bus lines with invalid demographic data or historical ridership data are removed. These included stations and bus lines with missing demographic data or not having ridership information up to the year 2020. Additionally, we exclude the years containing unusual long periods of zero ridership (e.g., if a line had a long period of zero ridership in 2004, all the data before 2005 are discarded). If certain bus lines showed clear signs of service changes (e.g., with sudden change of unusually high or low ridership for prolonged periods), their data are also removed from the study. For the bus system, only the lines operated for the entire week are used so they can be directly compared with rail ridership. Nonetheless, the selected bus lines still span the entirety of Chicago as shown in Fig. 5(b), ensuring that our analysis covers all geographic neighborhoods. After processing, we have complete datasets for 139 “L” stations and 62 bus lines. The summary statistics of socio-demographic data at the rail station level and bus route level are summarized in Table 7 in Appendix.

4. Methodology

To further understand the observed temporal variations of transit ridership during the pandemic, and to seek underlying reasons for spatial heterogeneity as shown in the previous section, a sequential statistical modeling framework is developed in this study, which integrates the following components:

1. A Bayesian structural time-series (BSTS) model, which considers the historical trend of transit ridership, including seasonality and holidays, to predict counterfactual transit ridership after March 15, 2020.
2. A dynamics model for daily transit ridership loss, inspired by Wang (2014), which captures the impacts of both people’s risk perception and external regulatory factors. The former includes objective risk measurements, e.g., daily confirmed cases and daily deaths (Wang, 2014), as well as media attention, e.g., Google Trends (Fenichel et al., 2013; Rogers, 2016). The latter includes executive orders, school closures, and remote working policies.
3. A linear regression analysis module, which builds connections between socioeconomic characteristics of city neighborhoods and people’s reactions toward the pandemic, using output from the dynamics model for daily ridership loss.

4 Because we only have line-level bus ridership data, here we assume for simplicity that every bus stop contributes to the ridership of a bus line equally, and the socio-demographic characteristics near a bus station can be represented by the data from the census tract that contains this station. As such, the number of bus stops per census tract can be used as the weight factor to aggregate the socio-demographic data along a bus line.
4.1. Bayesian structural time series for counterfactual prediction

Bayesian structural time series (BSTS) is an analysis technique that combines feature selection and time-series forecasting (Scott and Varian, 2014; Brodersen et al., 2015). In general, a structural time-series model contains three components: Kalman filtering for long-term trends and seasonal components, spike-and-slab regression for contemporaneous covariates, and Bayesian model averaging for the final model selection.

BSTS models can generally be defined by an observation equation that relates the observed time-series variables to a set of latent state variables, and a set of state equations which dictate how the latent state variables evolve over time under uncertainties. In this study, the observation equation connects the daily ridership on day $t$, $r_t$, with the following latent variables: (i) a semi-local linear trend, whose value on any day $t$ (denoted as $\mu_t$) is governed by a state equation involving a short-term increment (denoted as $\delta_t$), a long-term slope (denoted as $D$), and a learning rate of local trend (denoted as $\rho$, where $\rho < 1$); (ii) a day-of-week seasonality component, with the $s$-th element on day $t$ being denoted by $\tau_{s,t}$; (iii) a month-of-year seasonality component, with the $s$-th element on day $t$ being denoted as $\eta_{s,t}$, where the superscript $m$ represents “month”; and (iv) a vector of contemporaneous variables $x_t$ with static coefficients $\beta$, which captures the effects of special days such as holidays. In addition, a series of error terms are defined to capture the uncertainties, i.e., $\epsilon_t$, $\eta_{\mu,t}$, $\eta_{\delta,t}$, $\eta_{\tau,t}$, and $\eta_{\eta,t}$, and they are each assumed to follow a zero-mean Gaussian distribution with variances $\sigma_{\epsilon,t}^2$, $\sigma_{\eta_{\mu,t}}^2$, $\sigma_{\eta_{\delta,t}}^2$, $\sigma_{\tau_{s,t}}^2$, and $\sigma_{\eta_{\eta,t}}^2$, respectively. The BSTS model for counterfactual ridership prediction is written as follows,

\begin{align}
    r_t &= \mu_t + \gamma_{t}^{m} + \beta_{t}^{s} x_t + \epsilon_t, \\
    \mu_{t+1} &= \mu_t + \delta_t + \eta_{\mu,t}, \\
    \delta_{t+1} &= D + \rho(\delta_t - D) + \eta_{\delta,t}, \\
    \tau_{s,t+1} &= \sum_{s=1}^{7} \tau_{s,t} + \eta_{\tau,t}, \\
    \eta_{m,t+1} &= \sum_{s=1}^{12} \eta_{m,t} + \eta_{\eta,t},
\end{align}

where Eq. (2) defines the observation equation for ridership $r_t$; Eqs. (3) and (4) define the semi-local linear trend; and Eqs. (5) and (6) define the seasonality components.

To evaluate the BSTS models’ performance, we first use ridership data from a training set (e.g., those from 2001 to 2018) to train the BSTS models, and then predict the ridership data in a test set (e.g., those in 2019) with the trained models. The forecasting errors are measured with the weighted mean absolute percentage error (WMAPE), defined as follows:

\[
    \text{WMAPE} = \frac{\sum_{t} w_t |\hat{r}_t - r_t|}{\sum_{t} |r_t|},
\]

where $\hat{r}_t$ is the forecast of ridership on day $t$.

4.2. Dynamics model for ridership loss

As aforementioned, we consider daily COVID-19 deaths, daily normalized Google query volumes of COVID-19-related subjects, caution fatigue, remote learning/working, and stay-at-home executive orders as factors that have led to daily ridership variations during this pandemic.

Let the training starts on day 0 and ends on day $T$ (the range of training data), i.e., $t \in \{0, 1, \ldots, T\}$. Let an integer variable $d_t$ denote the number of reported deaths on day $t$; a positive variable $q_t$ denote the Google Trends score on day $t$; a binary variable $c_t$ be equal to 1 if remote learning/working is effective on day $t$, and 0 otherwise; a binary variable $s_t$ be equal to 1 if the stay-at-home order is effective on day $t$, and 0 otherwise. Similar to Wang (2014), we model the impacts of daily deaths and daily Google search volumes on transit ridership via two means, i.e., fresh fear and residual fear.

On day $t$, the reported daily deaths $d_t$ and the queries of COVID-19 topics through Google Trends $q_t$ together influence people’s perception of COVID-19-related risks, which directly induced ridership loss on the same day $t$, and such an effect is referred to as fresh fear. We assume coefficients $L_d$ and $L_q$ to capture the percentages of counterfactual ridership loss due to each reported death and each unit of Google Trends query score, respectively.

Fear does not dissipate instantly. It imposes a prolonged but decaying effect as time passes, and such a residual effect is referred to as residual fear. Thus, similar to Wang (2014), we assume that the residual effects of fear on day $t$ induced by the reported COVID-19 deaths and Google queries on a past day $t' < t$ diminishes over time via exponential multiplicative factors $e^{-\tau_d(t-t')}$ and $e^{-\tau_q(t-t')}$, respectively, where $\tau_d$ and $\tau_q$ are the corresponding diminishing rates.

The caution fatigue phenomenon says that people become less sensitive to fear (especially that from reported deaths). Hence, we hypothesize that people’s risk perception for deaths decreases with $t$ in a similar exponential manner with $f_d$ as the decreasing rate; i.e., $e^{-f_d t}$. The caution fatigue factor is not added to the Google Trends query terms because the score itself should reflect people’s awareness related to the pandemic, which in turn translates to ridership loss.

Finally, remote learning/working and stay-at-home orders are external factors for people to comply with when they are in effect. We thus focus on the direct ridership loss from these factors via coefficients $L_c$ and $L_s$, respectively.
In summary, the estimated ridership on day \( t \), denoted as \( \hat{r}_t \), can be calculated as follows,

\[
\hat{r}_t = r_t \left[ 1 - e^{-\alpha \sum_{t'=0}^{T} d_{t',L} \exp(\phi) - \sum_{t'=0}^{T} q_{t',L} e^{-\alpha (t-t')} - c_s L_s - s_s L_s} \right], \forall t.
\]

The values of all coefficients in Eq. (8) are estimated via a nonlinear regression model, such that the estimated value \( \hat{r}_t \), based on the counterfactual ridership \( \hat{r}_t \) from the BSTS model, is close to actual observations \( r_t \) in all days \( t \in \{0, 1, \ldots, T\} \). The nonlinear optimization module is implemented with the SciPy package in Python (Virtanen et al., 2020) to minimize the quadratic loss function, as follows,

\[
\min_{L_d, L_q, L_c, \alpha, \phi, q_d} \sum_{t=0}^{T} (r_t - \hat{r}_t)^2 \\
\text{s.t.} \quad \hat{r}_t \geq 0, \quad \forall t.
\]

where Eq. (10) enforces a set of nonnegativity constraints. It should be noted that using nonlinear optimization to obtain the coefficient values may lead to overfitting, due to noises and outliers. To ensure reliability of the model fitting, we use cross-validation to find the suitable stopping criterion for nonlinear optimization,\(^5\) as discussed in Arlot and Celisse (2010). Finally, the WMAPE metric is applied again to evaluate the error of the dynamics models.

4.3. Linear regression on socio-demographic factors

To investigate how the impacts of various pandemic-related factors vary across different urban areas and different socio-demographic groups, we next set up a series of linear regression models to reveal the relationships between key impact effect coefficients from the dynamics model (e.g., \( L_d \), \( L_q \), \( L_c \), \( \alpha \), and \( \phi \)), and socio-demographic and land-use characteristics. The default approach will be ordinary least square regression, but in case of need, issues such as heteroskedasticity and colinearity will be tested and addressed by other regression methods (e.g., generalized least squares).

5. Results and discussion

In the first step of the analysis, the BSTS model is applied to estimate the counterfactual ridership of all selected CTA rail stations and bus lines. Figs. 6(a) and 6(b) present observed and counterfactual ridership for all rail stations from March 15, 2020, to February 28, 2021, respectively. Similarly, Figs. 7(a) and 7(b) present the observed and counterfactual ridership for all bus lines, respectively. The histograms of WMAPEs for the counterfactual ridership of all rail stations and bus lines are presented in Figs. 8(a)–8(b). The WMAPEs for the BSTS model are calculated by using the ridership for the years 2001–2018 as a training data set and using the trained model to predict the 2019 ridership. The resulting mean WMAPE values across all rail stations and all bus lines are 0.210 and 0.144, respectively. The vast majority of WMAPE values, as presented in Fig. 8, are substantially smaller than 100%, indicating good fits of the BSTS models. Additionally, the Q–Q plots of the residuals are inspected for all rail stations and bus lines, and they generally follow a normal distribution. Table 2 presents the summary statistics of contemporaneous covariates coefficients, including mean, min, and max of coefficients across all rail stations and bus routes respectively, as well as the percentage of rail stations or bus routes with an inclusion probability (IP) equals to one. The coefficients capture the percentage reduction of daily ridership on holidays considered in the BSTS model. The results show that seven out of eight holidays should be included in the models for over 60% of the rail stations, and four out of eight holidays should be included over 60% of the bus routes. Here, to make the model results easy to compare, we include all eight holidays in the BSTS models for both rail stations and bus routes.

The results from the BSTS models are used as input into the nonlinear optimization problem Eq. (9)–(10), which is solved to fit the observed ridership for each rail station and each bus line. The histograms of the resulting WMAPEs for the dynamic model fit of all rail stations and bus lines are presented in Figs. 9(a) and 9(b). For the rail system, the mean WMAPE across all stations is 0.153. The dynamics models for bus system generally perform slightly better with a mean WMAPE value of 0.141. There are some extreme values and outliers, but those stations and bus lines experienced very low ridership both before and after the pandemic (i.e., less than 1000 daily passengers), and hence their data are not reliable against random fluctuations. It is expected that the models for bus system perform better than those for rail system because the bus ridership is obtained from all stops on a route, which, due to the law of large numbers, makes the data more robust to noises and outliers. To provide an illustration, the predicted and observed ridership curves for one rail station (ID: 710) and one bus line (ID: 50) are presented in Figs. 10(a) and 10(b), respectively, along with their respective residual errors in Figs. 10(c) and 10(d).

The summary statistic for the dynamics model parameters are presented in Table 3. The table also provides the percentage of stations and bus lines for which the model parameters are found to be statistically significant at a 95% confidence level. The impacts

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\(^5\) We randomly select five stations to look for the most suitable stopping criterion, by randomly partitioning the total study period \( T \) into four sub periods with equal size for each station and conducting 4-fold cross-validation. The reasons to choose 4-fold cross-validation include: (i) the dynamics model only requires the observed ridership and the counterfactual ridership on day \( t \), along with other input data, to predict the ridership on day \( t \); the ridership in the past is not considered, since the temporal trend of ridership has already been captured by the counterfactual ridership; and (ii) random partition ensures that both the training set and the validation set in four iterations of the 4-fold cross-validation include the ridership trend throughout the study period. In our numerical study, the stopping criterion that yields the least losses during the 4-fold cross-validation is \( 1E-4 \) for both the rail and the bus systems.
Fig. 6. Daily ridership of each rail station and the mean over all stations.

Fig. 7. Daily ridership of each bus line and the mean over all bus lines.

Fig. 8. WMAPE of the BSTS model in all bus lines and rail stations.
for bus. This indicates that, although the effect of reported deaths is initially higher for the bus system, it diminishes at a faster rate.

Then, the effect of $L$ for the dynamics model Eq. (8). The ridership loss due to the "fresh fear" for each daily reported death, $L_d$, is initially 0.890% for rail and 1.64% for bus. Then, the effect of $L_d$ dissipates by an exponential factor of $e^{-de}$, with $f_d$ equal to 0.0475 for rail and 0.219 for bus. This indicates that, although the effect of reported deaths is initially higher for the bus system, it diminishes at a faster rate than that of the rail system; see Fig. 11. On the other hand, each Google Trends score affects the rail ridership by $L_q = 0.0835\%$

### Table 2

| Holiday       | Rail          | Bus           |
|---------------|---------------|---------------|
|               | Mean | Min  | Max  | Stations with IP = 1 (%) | Mean | Min  | Max  | Stations with IP = 1 (%) |
| Christmas day | $-1.02E+03$ | $-5.75E+03$ | $0.00E+00$ | 72.22 | $-4.21E+03$ | $-1.08E+04$ | $0.00E+00$ | 79.73 |
| Independence day | $-1.16E+03$ | $-8.38E+03$ | $0.00E+00$ | 84.72 | $-2.40E+03$ | $-5.90E+03$ | $0.00E+00$ | 45.95 |
| Labor day     | $-2.06E+03$ | $-1.26E+04$ | $0.00E+00$ | 90.28 | $-3.02E+03$ | $-1.11E+04$ | $0.00E+00$ | 78.38 |
| Memorial day  | $-5.64E+02$ | $-6.10E+03$ | $0.00E+00$ | 43.75 | $-1.95E+03$ | $-7.17E+03$ | $0.00E+00$ | 62.16 |
| MLK day       | $-8.40E+02$ | $-5.43E+03$ | $0.00E+00$ | 69.44 | $-6.30E+02$ | $-9.85E+02$ | $0.00E+00$ | 5.41 |
| New Year day  | $-8.92E+02$ | $-5.38E+03$ | $0.00E+00$ | 68.75 | $-7.99E+02$ | $-2.70E+03$ | $0.00E+00$ | 18.92 |
| Presidents day| $-1.79E+03$ | $-1.11E+04$ | $0.00E+00$ | 86.11 | $-3.19E+03$ | $-1.06E+04$ | $0.00E+00$ | 70.27 |
| Thanksgiving day | $-1.71E+03$ | $-9.23E+03$ | $0.00E+00$ | 87.50 | $-1.20E+03$ | $-4.50E+03$ | $0.00E+00$ | 20.27 |

### Table 3

| Parameter | Rail          | Bus           |
|-----------|---------------|---------------|
|           | Mean | Min  | Max  | Significant for stations (%) | Mean | Min  | Max  | Significant for lines (%) |
| $L_f$     | $8.90E+03$ | $0.00E+00$ | $7.20E+01$ | 97.9 | $1.64E+02$ | $0.00E+00$ | $1.52E+01$ | 93.0 |
| $e_f$     | $2.79E+01$ | $2.13E+14$ | $9.42E+00$ | 84.4 | $2.46E+00$ | $0.00E+00$ | $9.84E+00$ | 54.0 |
| $L_s$     | $4.75E+02$ | $0.00E+00$ | $8.49E+01$ | 66.7 | $2.19E+01$ | $0.00E+00$ | $9.84E+01$ | 79.0 |
| $e_s$     | $8.35E+04$ | $0.00E+00$ | $2.59E+03$ | 96.5 | $7.46E+04$ | $0.00E+00$ | $3.02E+03$ | 87.0 |
| $e_r$     | $2.06E+00$ | $1.11E+08$ | $9.59E+00$ | 77.3 | $3.19E+00$ | $6.49E+12$ | $9.84E+00$ | 82.0 |
| $L_r$     | $6.62E+01$ | $3.43E+01$ | $8.94E+01$ | 100 | $5.36E+01$ | $3.09E+01$ | $6.92E+01$ | 98.0 |
| $e_r$     | $1.03E+02$ | $0.00E+00$ | $5.18E+02$ | 32.6 | $2.12E+02$ | $0.00E+00$ | $6.73E+02$ | 49.0 |

of policy related factors, i.e., $L_f$ and $L_s$, are easy to read from the summary table. The remote learning/work has induced an average daily ridership loss of about 66.2% for rail and 53.6% for bus after March 15, 2020, as captured by $L_f$. It shows that, generally, the bus ridership is less affected by the remote learning/work policies than the rail ridership. On the other hand, the percentage ridership losses related to the stay-at-home orders, as captured by $L_d$, for both bus and rail systems are less than 3% on average. The differences between these two policy factors, regarding both the estimates and the significance level, are very distinct, but expected, however. The remote work/learning policies eliminate the most commuting needs, which is a significant part of the daily ridership, and therefore, it is the major reason behind ridership reduction. On the contrary, the additional stay-at-home orders mainly limit the social activities, such as gatherings, parties, and close-contact group sports, which only take up a small portion of transit ridership. As a result, the impacts of stay-at-home orders on transit ridership, i.e., $L_s$, are relatively small, and it is only significant in 32.6% of the stations and 49.0% of the bus lines.

To get a clear idea of the relative magnitudes of impacts that people's risk perceptions and policy factors have on ridership reductions, Fig. 11 presents the average daily ridership loss (measured as a percentage between 0 and 1) across all rail stations and bus lines related to all factors (i.e., COVID-19 deaths, Google Trends, remote working/learning policies, and stay-at-home orders) in the dynamics model Eq. (8). The ridership loss due to the "fresh fear" for each daily reported death, $L_d$, is initially 0.890% for rail and 1.64% for bus. Then, the effect of $L_d$ dissipates by an exponential factor of $e^{-de}$, with $f_d$ equal to 0.0475 for rail and 0.219 for bus. This indicates that, although the effect of reported deaths is initially higher for the bus system, it diminishes at a faster rate than that of the rail system; see Fig. 11. On the other hand, each Google Trends score affects the rail ridership by $L_q = 0.0835\%$
Fig. 10. Dynamics model fit examples.

and bus ridership by $L_q = 0.0746\%$, indicating that ridership of both modes are influenced by access to the social media and news coverage at about the same level. Furthermore, the residual effect of fear due to both daily deaths and Google Trends scores, as captured by $\tau_d$ and $\tau_q$, are notably greater for the bus system than for the rail system. This indicates that the “residual fear” due to deaths and news coverage affects the rail ridership for longer periods of time. Fig. 11 also shows visually that, for the first 3 to 4 months of the pandemic, the total “fear” components (i.e., Reported deaths and Google Trends) led to about 18% rail ridership loss and 21% bus ridership loss, but their effects were reduced to only about 1% and 6% respectively by the end of the first year as a result of caution fatigue.

Next we conduct linear regressions to reveal how socioeconomic factors affect the values of $L_d, L_q, L_s$ and $L_c$. For each of the linear regressions, the Breusch–Pagan test is performed to check for heteroskedasticity, using the R package’s ‘lmtest’ function (Zeileis and Hothorn, 2002). Despite the fact that our observation units (e.g., catchment areas) are spatially heterogeneous in size, no strong evidence of heteroskedasticity is observed, probably because the dependent variables in these regression analyses, i.e., $L_d, L_q, L_s$ and $L_c$, are used in the dynamics model to estimate percentage ridership losses (which are bounded in value). Hence, the linear regressions are performed on all the explanatory variables in Table 1. To allow for nonlinear effects, the squares of these variables are also included in each regression, and their variable names end with “_2”. The results are presented in Table 4 (for the CTA rail system) and Table 5 (for the CTA bus system), which explain the impacts of socioeconomic and land use characteristics. For each regression model, the model starts with all possible explanatory variables, and then considers how deleting a variable affects either the Akaike information criterion (AIC) or the Bayesian information criterion (BIC). A backward search is performed on the explanatory variables under both criteria, and the model with the smallest leave-one-out cross-validation (LOOCV) root mean square error is selected at the end.

The CTA rail ridership regressions show that, overall, the socioeconomic characteristics best explain the effects of the remote learning/working policies, yielding an adjusted $R^2$ of 0.751 for the model on $L_c$. On the other hand, the impacts of stay-at-home executive orders $L_s$ are predicted with an adjusted $R^2$ of only 0.347. This difference is expected. The availability of remote learning/working are highly dependent on socioeconomic characteristics, e.g., job types, education level, and land use types. On the contrary, the stay-at-home orders forbid all non-essential travel for all people, and therefore, cannot be as effective in relating the socioeconomic and land use characteristics to the ridership. Furthermore, the adjusted $R^2$ values for $L_d$ and $L_q$ (capturing people’s fear levels) are 0.158 and 0.456, respectively, indicating a moderate level of correlation for $L_d$ and a very weak correlation for $L_q$. It is reasonable since the reported deaths can generally induce fear among all the public, but different population groups may have different accessibility to and beliefs in media coverage.
Fig. 11. Average ridership loss per day across all rail stations and bus lines due to different contributing factors.

Table 4
Linear regression results for CTA rail.

| Variable             | \( L_d \) Estimate | p-value | \( L_q \) Estimate | p-value | \( L_c \) Estimate | p-value | \( L_s \) Estimate | p-value |
|----------------------|---------------------|---------|--------------------|---------|--------------------|---------|--------------------|---------|
| (Intercept)          | 4.34E−01            | 1.22E−02| 1.06E−04           | 6.26E−01| −1.74E+00          | 9.61E−02| −8.09E−04          | 8.92E−01|
| prop_age_0_24        | −5.34E−01           | 5.13E−02| −4.94E−03          | 1.00E−03| −1.09E+00          | 3.0E−05 | −1.30E−01          | 2.44E−04|
| prop_age_25_39       | 1.13E+00            | 8.33E−03| 1.24E−02           | 5.70E−05| −1.96E+00          | 1.18E−03| 2.45E−01           | 1.66E−03|
| prop_white           | −7.02E−01           | 2.30E−02| 1.40E−03           | 1.30E−07| −1.80E−01          | 5.34E−06| −1.89E+00          | 9.63E−08|
| prop_black           | −4.54E−01           | 2.40E−03| 1.00E−03           | 1.30E−07| −1.09E+00          | 3.0E−05 | −1.30E−01          | 2.44E−04|
| prop_age_40_64       | −7.07E−01           | 2.44E−02| 1.24E−02           | 5.70E−05| −1.96E+00          | 1.18E−03| 2.45E−01           | 1.66E−03|
| prop_white           | 1.13E+00            | 8.33E−03| 1.24E−02           | 5.70E−05| −1.96E+00          | 1.18E−03| 2.45E−01           | 1.66E−03|
| prop_black           | −7.02E−01           | 2.30E−02| 1.40E−03           | 1.30E−07| −1.80E−01          | 5.34E−06| −1.89E+00          | 9.63E−08|
| prop_asian           | −4.54E−01           | 2.40E−03| 1.00E−03           | 1.30E−07| −1.09E+00          | 3.0E−05 | −1.30E−01          | 2.44E−04|
| prop_asian_2         | −7.07E−01           | 2.44E−02| 1.24E−02           | 5.70E−05| −1.96E+00          | 1.18E−03| 2.45E−01           | 1.66E−03|
| prop_poverty         | −1.73E−01           | 6.65E−02| −7.78E−03          | 8.55E−05| −1.96E+00          | 9.63E−08| −1.89E+00          | 1.18E−03|
| prop_R_manuf         | −3.32E−01           | 6.21E−02| −7.78E−03          | 8.55E−05| −1.96E+00          | 9.63E−08| −1.89E+00          | 1.18E−03|
| prop_R_trade         | 2.97E+00            | 4.96E−03| −7.78E−03          | 8.55E−05| −1.96E+00          | 9.63E−08| −1.89E+00          | 1.18E−03|
| prop_R_health_2      | −3.32E−01           | 6.21E−02| −7.78E−03          | 8.55E−05| −1.96E+00          | 9.63E−08| −1.89E+00          | 1.18E−03|
| prop_LU_residential_2| −5.01E−01           | 1.34E−02| −1.16E−02          | 1.12E−03| −2.54E−02          | 1.92E−02| −1.83E+00          | 2.30E−04|
| prop_LU_education    | −2.55E+00           | 5.86E−03| 2.95E−03           | 6.22E−03| 2.97E−01           | 1.42E−02| 2.45E−01           | 1.66E−03|
| prop_LU_transportation| −5.01E−01          | 1.34E−02| −1.16E−02          | 1.12E−03| −2.54E−02          | 1.92E−02| −1.83E+00          | 2.30E−04|
| Adjusted \( R^2 \)   | 0.158               | 0.456   | 0.751              | 0.347   |                    |         |                    |         |

Regarding the regressions for CTA bus ridership, all models (except the one for \( L_c \)) have higher adjusted \( R^2 \) values, as compared to those for CTA rail ridership. The \( L_q \) model has the highest adjusted \( R^2 \) value of 0.878, while the \( L_d \), \( L_c \), and \( L_s \) models have adjusted \( R^2 \) values of 0.326, 0.630, and 0.479, respectively. This indicates that, different from the rail models, socioeconomic
variables best explain the ridership loss due to the public fear induced by news media. For factors related to public fear perceptions in the bus system, the socioeconomic variables can better explain the impacts of news media than that of daily reported deaths; and for regulatory events, the socioeconomic variables can better explain the impacts of remote working/learning than that of stay-at-home orders. These findings are consistent with those from the rail models.

Since greater values of positive dependent variables $L_x$, $L_y$, $L_z$, and $L_r$ imply higher percentages of ridership loss, a positive (negative) coefficient in the linear regression models indicates that an increase of its corresponding independent variable leads to more (less) ridership loss. When an independent variable and its square both appear in a regression analysis and their coefficients have different signs (as observed for all our cases of the rail system and most cases of the bus system; see Tables 4 and 5), this independent variable has a diminishing marginal influence. In this study, our correlation analysis focuses on the cases that (i) independent variables are statistically significant in the model at a 95% confidence interval (with the p-value < 0.05); and (ii) an independent variable has only the linear term, has only the quadratic term, or has both linear and quadratic terms but their coefficients have the same sign in the regression model, so that the correlation between the independent variable and the dependent variable is monotonic.
The correlations in both the rail system and the bus system are summarized in Table 6. The considered age-related variables are all found to have significant correlations. In particular, we notice that the proportion of population aged 25–39 is positively correlated with $L_i$ in both bus and rail systems. For race distribution, it is noted that the proportion of white population is positively correlated to $L_\text{q}$ in the rail system and to $L_a$ in the bus system, and that of Asian population is positively correlated to $L_a$ in the rail system and to $L_d$ in the bus system. These two racial groups are similar in terms of having a positive correlation with ridership loss for both bus and rail. The proportion of black population is negatively correlated with $L_a$ in the rail system, which agrees with the findings from the past literature (Fissinger, 2020) and the preliminary analysis as shown in Fig. 3. In the bus system, the proportion of black population is negatively correlated with $L_d$ and positively correlated with $L_q$ in the bus system, indicating that black population could be relatively more susceptible to the daily reported deaths and less susceptible to the news coverage (as compared to the benchmark “other” racial groups).

We can also draw insights from the influence of occupation and land use variables. As the manufacturing factories and other industrial facilities usually require staff to work in-person, it is reasonable that the proportion of industrial land use is negatively correlated with $L_a$ in both bus and rail systems. However, we also note that the proportion of workers in the manufacturing industry is positively correlated with $L_a$ in the rail system; a possible reason is that the occasional factory shutdown, e.g., due to the COVID-19 outbreak within the factories (Wayland, 2020; Graber, 2020), and due to the lack of raw materials caused by supply chain challenges during the pandemic (Pete, 2021), reduces the travel demand. Likely due to similar requirements of in-person working in the wholesale/retail trade businesses, the proportion of residents in the wholesale/retail trade businesses is negatively correlated with $L_a$ in the rail system, and the proportion of workers in the wholesale/retail trade industry is negatively correlated with $L_a$ and $L_q$ in the bus system. For education-related activities, the proportion of educational land use is positively correlated with $L_a$ in both rail and bus systems, as expected. However, the proportions of workers and residents with education-related occupation do not exhibit distinct patterns. The proportion of residents with a healthcare-related occupation is positively correlated with $L_d$ in the rail system, possibly due to health workers’ impaired ability to work after infection and their fear for using public transit, as observed in Ives et al. (2009). The proportion of workers with a healthcare-related occupation is negatively correlated with $L_q$ in the bus system, which is expected since the healthcare workers are required to work in-person, and therefore, the remote working/learning induce less changes in their travel behaviors. In addition, the proportion of commercial land use is negatively correlated with $L_a$, probably because people still go to commercial facilities for essential trips during the pandemic, e.g., shopping daily supplies, which is not limited by the stay-at-home orders. The proportion of transportation land use is negatively correlated with $L_d$ in both rail and bus systems, and the proportion of open space is negatively correlated with $L_a$. This is also reasonable. A higher percentage of transportation-purposed or open space implies a lower percentage of trip origin/destination areas (e.g., residential areas, schools, and offices), which in turn leads to less ridership loss from pandemic-related fear or remote working/learning policies.

As a final remark, the results from the dynamics model show that the magnitude of ridership loss due to executive orders is significantly higher than that of public fear, which means that the executive orders will also play a vital role in the future recovery of ridership. Studies in the past have shown that the part of fear-caused ridership loss can often be recovered within a year (Wang, 2014; Sung, 2016), so these results may further suggest that once the remote work/study orders are lifted, the pre-pandemic ridership levels could be achieved soon afterwards. However, this estimate does not consider the “new normal” for those people whose jobs

| Variable                  | Rail                  | Bus                  |
|---------------------------|-----------------------|----------------------|
| prop_age_0.24             | Positive              | $L_i$                |
| prop_age_25.39            | Positive              | $L_i$                |
| prop_age_40.64            | Negative              | $L_d$                |
| prop_white                | Positive              | $L_i$                |
| prop_black                | Negative              | $L_d$                |
| prop_asian                | Positive              | $L_i$                |
| prop_R_Manuf              | Negative              | $L_a$                |
| prop_W_Manuf              | Positive              | $L_i$                |
| prop_R_Trade              | Negative              | $L_i$                |
| prop_W_Trade              | –                     | –                    |
| prop_W_Edu                | Negative              | $L_q$                |
| prop_R_Edu                | Positive              | $L_i$                |
| prop_R_Health             | Positive              | $L_d$                |
| prop_LU_commercial        | Negative              | $L_i$                |
| prop_LU_industrial        | Negative              | $L_d$                |
| prop_LU_education         | Positive              | $L_i$, $L_d$         |
| prop_LU_transporation     | Negative              | $L_i$                |
| prop_LU_openspace         | –                     | –                    |

Table 6: Summary of correlations in rail and bus systems.
shifted to remote or hybrid work style permanently. Moreover, the regression results from this paper highlight that the impacts of COVID-19 on ridership are highly heterogeneous over space, not only because areas differ by their demographic characteristics (as other studies have shown), but also because there are influences of other factors such as the local population’s job characteristics and land use types. In addition, the results also show vast differences between the ridership losses in the bus mode versus those in the rail mode, and even among those of the same mode that are caused by different aspects during the pandemic, i.e., death counts, media coverage and executive orders. Hence, efforts to recover ridership must be differentiated across areas (and modes).

6. Discussion and conclusion

This study proposes a sequential statistical modeling framework to capture contributing factors behind public transit ridership variations over time and space under major disruptions caused by COVID-19. This framework integrates (i) a Bayesian structural time series (BSTS) model to estimate counterfactual ridership based on the historical data; (ii) a dynamics model to explain the observed ridership variations with both instant and prolonged effects from events such as daily reported deaths, media attention, remote work/learning, and stay-at-home executive orders; and (iii) a linear regression model to draw connections between socioeconomic and land use characteristics and the aforementioned instant effects. This study uses data from the Chicago Transit Authority’s bus and rail systems to draw insights.

Results from the dynamics model indicate that most of the ridership reduction in both CTA bus and rail systems is associated with executive orders. All fitted parameters of the dynamics model, except for the impacts of stay-at-home orders, \( L_s \), are statistically significant in explaining the observed ridership reductions for the majority of rail stations and bus routes. Therefore, it is expected that once all schools fully reopen and all the work/travel restrictions have been lifted, the CTA’s rail and bus ridership may immediately recover by large percentages of the pre-pandemic levels. In addition, it is noted that the bus ridership is relatively less sensitive than rail ridership on average. The executive orders contributed to an average rail ridership loss, i.e., \( L_c + L_s \), of 67.2% across all stations, while bus ridership is only reduced by an average of 55.7%. Meanwhile, it is important to note that the above finding does not consider the “new normal”, as many companies is adapting to long-term hybrid working style and there could also be substantial commuting behavior changes among certain passengers. In other words, it is possible that some riders who used to ride on a daily basis may not immediately return to that routine. Yet, just as other studies in the past have shown, our models also indicate that fear-based ridership loss (due to those with strong risk perception and self-protective behavior) also recovers within a few months.

The linear regressions show that the socioeconomic and land-use characteristics can (i) predict people’s reactions to news media better than those to reported deaths, and (ii) capture the impacts of remote learning/working better than those of stay-at-home orders, for both bus and rail modes. The results also highlight the vast differences among types of ridership losses, and between modes. However, the common observations from both bus and rail systems provide meaningful insights on the influence of socioeconomic and land use characteristics; e.g., the positive correlation between the proportion of population aged 25–39 and \( L_c \), for both modal systems (i.e., exhibiting relatively more significant travel behavioral changes induced by the stay-at-home orders on people aged 25–39 as compared to other age groups); the negative correlation between the proportion of industrial land areas and \( L_c \), for both systems (indicating that the commuting behaviors of factory workers are less likely impacted by remote working as compared to others); and the positive correlations between the proportion of educational land use and \( L_c \), in both systems (implying that travels related to the education industry have been severely affected by online learning); and the negative correlation between the proportion of transportation-purposed land use and \( L_d \), for both systems. In addition, both the proportions of the white populations and Asian populations tend to be positively correlated to the ridership reduction for both rail and bus systems, while the proportion of the black population is negatively correlated with \( L_c \) in the rail system. These findings are generally consistent with those in the literature.

The results from this study have direct and important implications for transit agencies. First, it is shown that passengers have direct reactions to the evolution of the pandemic (i.e., daily reported deaths and news coverage). At the beginning of the pandemic, the “fear” led to about 18% rail ridership loss and 21% bus ridership loss; Yet, these numbers were respectively reduced to only 1% and 6% by the end of the first year as a result of caution fatigue. It is possible that this observed caution fatigue is a consequence of CTA’s cleaning and sanitation practices (i.e., people feeling more comfortable traveling) (Chicago Transit Authority, 2021). Nonetheless, it is clear that these reactive practices alone are not enough to fully recover transit ridership since the major ridership loss appears to be induced by remote work and stay-at-home executive orders. Therefore, transit agencies may need to leverage their ridership recovery efforts through proactive policy instruments and incentive programs that can stimulate demand among those who have changed their commuting needs. These types of proactive recovery programs have seen success in Toronto and Hong Kong during previous pandemics such as the Severe Acute Respiratory Syndrome (SARS) (Hong Kong Mass Transit Railway, 2004; Toronto Transit Commission, 2005; Shier, 2020). These strategies may include partnerships with the private sector, launching discount programs and promotional activities, improving service quality during the peak hours, or advertisement campaigns (Daniels, 2003). Such strategies may also encourage those with hybrid work or school environments (i.e., with the freedom to choose) to select the in-person experience and commute again.

The result from this study also highlights the importance of considering socioeconomic and demographic factors while planning transit services during or after the pandemic. For example, the ridership loss due to remote work orders is highly related to the socioeconomic and job characteristics of the population, and it vary significantly across neighborhoods. Therefore, a way to facilitate the ridership recovery could be targeting specific geographic areas and job industries which were particularly affected during the COVID-19 pandemic. Nonetheless, it is important to consider that such policies must be carefully designed for equity considerations.
Acknowledgments

The authors thank the editors and the reviewers for providing very helpful comments on the paper. This research was supported in part by the Illinois Department of Transportation via Illinois Center for Transportation project ICT R27-SP45. The authors gratefully acknowledge the valuable feedback from all members of the Technical Review Panel, led by Mr. Charles Abraham (Illinois Department of Transportation) and Ms. Jessica Hector-Hsu (Regional Transit Authority). The contents of this paper reflect the view of the authors, who are responsible for the facts and the accuracy of the information presented herein. The contents do not necessarily reflect the official views or policies of the Illinois Center for Transportation, the Illinois Department of Transportation, or the Federal Highway Administration. This paper does not constitute a standard, specification, or regulation.

Appendix. Statistics of socio-demographic data

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