Understanding the Recovery of On-Demand Mobility Services in the COVID-19 Era

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Abstract
The COVID-19 pandemic and its related events (e.g., lockdown policies, vaccine distributions) have caused disruptive changes in travel patterns and urban mobility services. Cities need to understand the impacts of these factors on mobility activities for taking effective actions to restore/reform urban transportation systems and prepare for future shocks. In this study, we investigate the correlations between the COVID-19 related factors and the usage of on-demand mobility services (OMS, i.e., street-hailing, ride-hailing, and bike-sharing) through a two-step framework. In the first step, we construct low-dimensional representations, called mobility signals, of multivariate mobility data which provide a temporal understanding of the variation of trips across different modes. Then the Bayesian structural time series model is utilized to estimate the regression coefficients and inclusion probability of different time-varying factors including COVID-19 cases, policies, and vaccination rates in predicting each mobility signal. This framework is adopted in New York City (NYC) and Chicago, two example cities that have been significant affected by COVID-19 disruptions and that have comprehensive on-demand mobility services. The results suggest an asymmetrical influence of COVID-19 related policies to the usage of OMS: the mobility/business restrictions can trigger fast and consistent decrease of ridership, but lifting these restrictions does not result in a fast rebound. Our analyses further uncovers the heterogeneity of spatial impacts of different COVID-19 related policies. A one-year prediction of OMS usage is conducted and the results suggest a highly uncertain future of the ride-hailing and street-hailing services, and relatively stable bike-sharing usage in the near future.

Keywords COVID-19 · On-demand mobility · Ridehailing · Bikesharing · Low-rank approximation · Bayesian structural time series

Introduction
The COVID-19 pandemic has caused an unprecedented disruption in urban mobility systems. During the first outbreak of COVID-19 in early 2020, many cities have seen a drastic drop in the number of trips among all transport modes (Engle et al. 2020; Lee et al. 2020; Armstrong et al. 2020; Yabe et al. 2020a). Following this drop is the slow recovery process (Nouvellet et al. 2021) that is full of uncertainty associated with the relaxation of the restrictions, the changes in public health intervention, and potentially the new waves of COVID-19 cases. In many places, the loss of the number of trips is still far from fully recovered even after one and a half years of the first outbreak. For example, the subway ridership in New York City is still reported to be around 60% to the pre-pandemic level till November 2021 (NYC Metropolitan Transportation Authority 2021), and the ridership of ride-hailing (e.g., Uber and Lyft) in September 2021 has just recovered to 63% to the value in September 2019 (NYC Taxi and Limousine Commission 2021).

Such phenomena place severe challenges to the restoration and reform of urban transportation systems. First, for urban mobility services such as public transit and ride-hailing, the dramatic reduction of travel demand can reduce the funding of service providers (in the US), leading to the shrinkage of service capacities which may hinder their recovery (Aloi et al. 2020) and further leading to a long term deterioration of mass transit system. Second, the pandemic is likely to change the citizens’ travel behavior...
and their preferences to different travel modes, resulting in a significant change of travel demand patterns (Sharifi and Khavarian-Garmsir 2020; Przybylowski et al. 2021). Third, the pandemic can alter the competition and substitution among different travel modes. Without proper investigation and intervention, such competition may lead to unwanted results such as additional congestion and pollution (Ward et al. 2021; Qian et al. 2020a). Finally, we need a framework to understand how the transportation systems recover during disruptions such as COVID-19 which do not physically impact the infrastructure but lead to significant changes in the ridership. Thus, it is critical to understand the recovery process of different modes and the impacts of corresponding factors.

Existing studies investigated urban mobility during COVID-19 through multiple data sources ranging from individual visits/trajectories (Yabe et al. 2020a; Basu and Ferreira 2021; Teixeira and Lopes 2020; Hu et al. 2021; Nian et al. 2020) to aggregated mobility reports (Bucsky 2020; Engle et al. 2020; Aloï et al. 2020; Falchetta and Noussan 2020), which provided valuable insights into the status quo and the potential future scenarios in different stages of the pandemic. However, limited attention is focused on quantifying the impacts of the time-varying factors (e.g., policies, events) and the interactions between different travel modes. It is worth noting that these impacts and interactions are essentially heterogeneous across the urban space (Hu et al. 2021), and the analyses based on single travel mode or aggregated reports cannot fully appreciate these aspects. Hence, besides the time dimension, the data also needs to contain the dimension of space and travel modes and it is necessary to consider a multivariate time series with time-varying factors.

A general framework of handling the time series with explanatory time-varying factors (i.e., predictors) is the structural time series (Harvey and Shephard 1993) model, which allows flexible components of modeling the time series data. The recent advances in this framework have introduced Bayesian statistics to estimate the coefficients of different predictors, which enable a sparse choice among a large set of predictors and generate the corresponding inclusion probability of different predictors (Scott and Varian 2014). The Bayesian time series (BSTS) model has been applied to explore the factors that influence the initial claims for unemployment (Scott and Varian 2014), sea level (Przybylowski et al. 2021), Bitcoin’s price, and stock portfolio (Jammalamadaka et al. 2019). We take advantage of this technique to investigate the influence of different COVID-19 related policies and events on the demand patterns of different modes in the on-demand mobility sector in New York City (NYC) and Chicago.

In this study, we make contributions to analyzing the dynamics of the OMS (i.e., taxis, for-hail vehicles, and bike-sharing) ridership with respect to the COVID-19 related factors. First, we propose a novel two-step framework to model the relationship between multivariate time series and a large group of predictors. In the first step, a dimensionality reduction approach called weighted low-rank approximation (WLRA) is applied to construct the low-dimensional mobility signals and static features of demand patterns. Then the BSTS model is utilized to estimate the regression coefficients and inclusion probability of different predictors in predicting the mobility signals. Second, we create three types of policy indicators to capture different potential dynamics of the policy impacts. Third, we apply our method to the OMS in New York City (NYC) and Chicago, which provides insights on how different factors influence the demand of

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1 See https://arxiv.org/ftp/arxiv/papers/1706/1706.01437.pdf.
OMS services and the interactions between different modes. Figure 1 illustrates the overview of this study. By fitting the OMS demand with COVID-19 related factors and other background information, we understand the influences of different factors and the potential future recovery processes.

The rest of this paper is organized as follows. In the next section, we describe the data used in this study and summarize some basic statistics related to the COVID-19 timelines in NYC and Chicago. Following section presents the detail of our methods shown in Fig. 1. In the next section shows the key results generated by the proposed method. Following section is the related work. In the next section, we summarize our findings and discuss the policy implications.

Datasets

COVID-19 Cases, Vaccination Rates and Policies

The COVID-19 cases and vaccination data are collected from two sources. For NYC, the number of daily new cases and total distributed vaccination doses data are downloaded from the coronavirus data repository published by the NYC Department of Health and Mental Hygiene (https://github.com/nychealth/coronavirus-data). For Chicago, we obtain the COVID-19 daily case and vaccine data from Chicago open data platform (https://data.cityofchicago.org/).

The records of COVID-19 related policies are collected and mutually confirmed from three sources: the Centers for Disease Control and Prevention (CDC) websites of NYC and Chicago, the literature (Bian et al. 2021; Armstrong et al. 2020), and the news. To facilitate the analyses, we organize the policies into four categories. The first category is the public health (PH) related policy, including the policies like the declaration of public health emergency and mandatory masking. The second type is the mobility restriction (MR) policy that makes direct restrictions on citizens’ daily mobility activities. The third category is the business restriction (BR) policy under which some businesses are not allowed to open during a certain time of the day. The fourth one is the overlapping (RO) policy that usually comes after the MR and BR policies with some restrictions relaxed. Table 1 summarizes the COVID-19 related policies in NYC and Chicago.

During the data collection, we also notice that there exists policies related to specific transportation modes. For example, Uber and Lyft, two of the largest ridesharing companies, banned their ridepooling option in both NYC and Chicago on March 17, 2020. In addition, during the stay-at-home order in Chicago, Divvy, the bikesharing provided 50% discount for the annual membership, and 30-days free bikeshare rides for critical healthcare workers (Chicago Mayor’s Press Office 2022). However, incorporating these mode-specific policies is challenging. First, these policies are highly overlapped with some master policies (e.g., the suspension of ridepooling and the stay-at-home policy), which can make the model to attribute the influence of the master policies to the mode-specific ones and vice versa. Second, some mode-specific policies may have delayed impacts. Take the 50% bikesharing annual membership discount as an example, it may not influence the number of bikesharing trips during the early outbreak of the pandemic with strict mobility/business restrictions, but it can benefit the bikesharing usage several months later when the mobility/business restrictions were lifted. Both challenges require additional prior knowledge on how users respond to these mode-specific policies, which is not available in this study. Hence, instead of including these mode-specific policies as independent COVID-19 related policies, we merge them with the existing ones and note them in Table 1.

From Table 1, it can be seen that both cities followed a similar flow of policies: The early policies altered the public health instructions and made direct restrictions on mobility activities by introducing social distances and closing non-essential businesses. Then the later policies updated the public health instruction and slowly lift the restrictions assigned in the early stage. During the 2020 winter, weaker restrictive policies were adopted to contain the virus transmission. The differences between the policies adopted in NYC and Chicago are that in Chicago, the stay-at-home policy did not explicitly instruct the close of non-essential businesses, but the PAUSE policy in NYC did; during the winter in 2020, NYC suspended indoor dining, but Chicago introduced a business curfew of all non-essential businesses.

Mobility Data

The mobility data of on-demand mobility systems are gathered from four different sources: the NYC for-hail vehicles (FHV) and taxis data are downloaded from the NYC Taxi & Limousine Commission; the Chicago rideshaling and street-hailing data are downloaded from the Chicago Open Data website the bikesharing system (BSS) data are collected from the corresponding bike-sharing programs called NYC Citi Bikes; and Chicago Divvy Bikes. The latest date with data available for NYC is July 31, 2021. Therefore, for this study, we build our model based on the OMS trip data from January 1, 2019, to July 31, 2021.

For each trip record, we use the information of the departure time, origin location/zone, and destination location/zone. Note the data from NYC and Chicago have different
spatial granularity: the taxi and FHV trip records in NYC provides the taxi zones which have the size similar to the zip code zone, while in Chicago, the taxi and FHV trip records are located by the corresponding census tracts (high missing rate) and community zones (low missing rate). To keep the consistency between the analyses of two cities, all the trip records are aggregated into daily inbound and outbound ridership at the community level by different modes. Given NYC has 71 community districts and Chicago has 77 communities, we obtain two multi-variate time series with the dimension as 71 (communities) × 2 (directions) × 3 (modes) for NYC and 77 × 2 × 3 for Chicago.

Figure 2 A presents the changes of daily trips for different modes, COVID-19 daily new cases, daily distributed vaccination doses, and COVID-19 related policies from February 2020 to July 2021. The changes in public transit are calculated from the data published by Metropolitan Transportation Authority and Chicago Transit Authority.

| City       | Policy                        | Index | Start date | End date | Notes                                                                 |
|------------|-------------------------------|-------|------------|----------|----------------------------------------------------------------------|
| NYC        | State of Emergency            | PH1   | 3/7/2020   | 6/24/2021| Nonessential foreign travel for city employees banned on 3/8/2020, ridepooling banned on 3/17/2020 |
|            | PAUSE (Stay-at-home)          | MR1   | 3/22/2020  | 5/15/2020| All non-essential businesses closed, no non-essential gathering, practice social distancing, bus became free until 8/30/2020 |
|            | Mask mandate                  | PH2   | 4/17/2020  | –        | Mask are required in public or in situation when social distancing cannot be maintained |
|            | One-week curfew               | MR2   | 6/1/2020   | 6/6/2020 | Vehicle traffic banned in Manhattan below 96th street from from 8pm to next day’s 5 am |
|            | Phase 1 reopening             | RO1   | 6/8/2020   | 6/21/2020| Non-essential businesses (i.e., constructions, manufactures, wholesalers, outdoor businesses) are allowed to resume, restaurants and bars are allowed to offer takeout and delivery |
|            | Phase 2 reopening             | RO2   | 6/22/2020  | 7/5/2020 | Several indoor businesses (i.e., outdoor dining, hair salon, offices, real estate firms, vehicle sales, and in-store retail) are allowed to reopen with limits on capacity and social distancing |
|            | Phase 3 reopening             | RO3   | 7/6/2020   | 7/19/2020| Additional businesses including personal care and “low-risk” youth sports are allowed |
|            | Phase 4 reopening             | RO4   | 7/20/2020  | –        | Entertainment, sports, and religious facilities are allowed to resume operating. The indoor dining is allowed with limits to 25% capacity |
|            | Cluster zone restriction      | MR3   | 10/6/2020  | 1/13/2021| Limit social gathering, school and require testing for zones based on three level of restrictions |
| Chicago    | Disaster proclamation         | BR1   | 12/14/2020 | 2/14/2021| End with 25% capacity allowed |
|            | Stay-at-home                  | PH1   | 3/9/2020   | –        | Ridepooling banned on 3/17/2020 |
|            | Liquor sales curfew           | MR1   | 3/21/2020  | 6/2/2020 | No more than ten people gathering, practice social distancing |
|            | Mandate mask                  | BR1   | 4/8/2020   | 5/18/2021| A curfew for all liquor sales to 9 p.m., rear-door boarding on buses on 4/9/2021 to 6/19/2020 |
|            | Phase 3 (Phase of reopening)  | PH2   | 5/1/2020   | –        | Mask is required when people must leave their home or report to work for essential operations |
|            | Phase 4                       | RO1   | 6/3/2020   | 6/23/2020| Non-essential businesses (i.e., constructions, manufactures, wholesalers, outdoor businesses) are allowed to resume, restaurants and bars are allowed to offer takeout and delivery. Personal care services are allowed to provide outdoor or one-to-one services. Retail can open with capacity limits |
|            | None-essential Business curfew| RO2   | 6/24/2020  | 5/7/2021 | All outdoor recreation is allowed to open. Several indoor businesses (i.e., bars, restaurants, personal care services, cinema, and theaters) are allowed to open with capacity limits |
|            | Stay-at-home (advisory)       | BR2   | 10/23/2020 | 1/31/2021| From 10:00 p.m. to 6:00 a.m. for all non-essential businesses, and bars without a retail food license will no longer be able to serve customers indoors |
|            | Bridge phase of Phase 5       | MR2   | 11/16/2020 | 1/22/2021| All sectors of the economy reopen with new safety guidance and procedures |
|            |                                | RO3   | 5/8/2021   | –        | All sectors of the economy reopen with new safety guidance and procedures |

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6 See https://new.mta.info/coronavirus/ridership.
The dots show the changes of daily ridership changes when compared with the pre-COVID observations in 2019, and the lines are the smoothed values based on 28-days (for BSS) or 14-days (for other modes) moving average. The red shaded area shows the daily new cases of the COVID-19 cases, and the green area shows the daily new distribution vaccine doses. It can be observed that the daily ridership of different modes plunges in March 2020, and most of the modes have not been fully recovered within the study period, except bike-sharing. In both cities, two waves of COVID-19 cases can be observed. Although the first wave is clearly correlated with the decline of mobility, the relationship between the COVID-19 cases and mobility is rather subtle in the second wave. Finally, we note that the usage of BSS exhibits stronger fluctuations than other modes’. This is because the size of bikesharing trips is one order of magnitude smaller than FHV and taxi trips and is strongly influenced by weather. For example, during the North American winter storm in February 2021, one can observe a sudden drop in the usage of BSS caused by extreme weather.

### Historical Weather Data

We include the historical weather data because previous studies suggest that some time-varying factors like the maximum daily precipitation (PRCP), maximum temperature (TMAX), and minimum temperature (TMIN), can significantly influence non-motorized activities (Ermagun et al. 2018; Zhang and Fricker 2021). The historical weather data is collected from the National Oceanic and Atmospheric Authority.

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7 See [https://www.transitchicago.com/ridership/](https://www.transitchicago.com/ridership/).
Administration. Since the weather data is collected by different weather stations, we first query the stations within the study region for each city, then take the average over the stations with complete records of historical data to obtain the input variables. Finally, we create a new predictor TRNG (the range of temperature) as the difference between TMAX and TMIN because TMAX and TMIN are highly linear correlated.

**Methodology**

**Weighted Low Rank Approximation for Multivariate Time Series**

Since the mobility data are high-dimensional vectors, dimensionality reduction is applied to reduce the number of parameters in the BSTS models in later steps. The common tools of dimensionality reduction include low-rank approximation (LRA), singular spectrum analysis (Golyandina et al. 2018), and neural network (Wang et al. 2016). Among these tools, the neural network requires significantly more data to train so it is not suitable here; singular spectrum approximation can be viewed as the extension of LRA that considers the autocorrelation with a predefined time lag. Here we use LRA since the autocorrelation can also be modeled in the structural time series model.

Low-rank approximation (LRA) allows representing a multivariate time series with a small number of factors. The premise of using LRA is that there exists a high level of data duplication in observations, which is clearly true for the ridership data as most trips are corresponding to repetitive activities like commuting and shopping. Weighted low-rank approximation (WLRA) extends the LRA approach by introducing a weight matrix to balance the goals of approximating different elements.

Consider a multivariate time series \( \{y(t) | t = 1, \ldots, m\} \) with each observation \( y(t) \) be a \( n \times 1 \) column vector, and \( y_i(t) \) is the \( i \)th element of \( y(t) \). Given the weight matrix \( W \), the WLRA problem can be described as

\[
\min_{L,R} \sum_{i=1}^{m} \sum_{t=1}^{n} W_{i,t}(y_{i}(t) - (LR^T)_{i,t})^2,
\]

where \( L \) and \( R \) are matrices with the size as \( m \times k \) and \( n \times k \) respectively, and \( k \) is the target number of dimensions. Here we name \( k \) as the number of signals. The objective is to minimize the weighted error of reconstructed time series using \( L \) and \( R \). When \( W \) is of rank one, the WLRA problem can be solved analytically using singular value decomposition (SVD) (Srebro and Jaakkola 2003). To be specific, consider a weight matrix \( W_{\text{diag}} \) with each column to be the same \( n \times 1 \) vector \( w \), and the time series data \( Y = [y(1), y(2), \ldots, y(m)]^T \). Denote \( \cdot \odot \) as the element-wise multiplication. Given the following SVD results for the weighted data matrix \( Y \odot W = [w \odot y(1), w \odot y(2), \ldots, w \odot y(m)]^T \) as

\[
Y \odot W = U_{\text{mxr}}S_{\text{mxr}}V_{\text{mxr}}^T = \sum_{j=1}^{r} \sigma_j U_j V_j^T,
\]

where \( S \) is a diagonal matrix with the \( j \)th diagonal element as \( \sigma_j (\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_r) \). \( U \) and \( V \) are collections of orthogonal unit vectors, \( U_j \) and \( V_j \) are the \( j \)th column vector of \( U \) and \( V \) respectively, \( r \) is the rank of \( Y \odot W \). The solution matrices \( \hat{L} \) and \( \hat{R} \) of the WLRA problem can be written as

\[
\hat{L} = [U_1, U_2, \ldots, U_k], \quad \hat{R} = [\sigma_1 V_1, \sigma_2 V_2, \ldots, \sigma_k V_k]^T.
\]

Furthermore, \( U_j \) captures the temporal dynamics of a certain group of trip demand represented by \( \sigma_j U_j V_j^T \). For real-world data with repetitive patterns, some small \( k \) \( (k < r) \) would be sufficient to approximate the original multivariate time series with enough precision.

We name \( U_j \) as the \( j \)th mobility signal. Instead of fitting and predicting the original time series, we train the Bayesian structure time series (BSTS) model with \( U_{j, \beta} = 1, 2, \ldots, k \), then reconstruct the target time series via (2) and the element-wise inverse of the weight matrix \( W \).

**Number of Signals**

There exists a trade-off for selecting the number of signals \( k \). On the one hand, large \( k \) means better reconstruction quality in (2). On the other hand, as \( k \) increases, the marginal benefits of reconstruction quality decrease, and some mobility signals may capture only the white noise. To choose \( k \) economically, we use the elbow method with respect to the reconstruction quality measured by root mean squared error (RMSE) and mean absolute error (MAE) the reconstructed time series.

**Bayesian Structural Time Series Model**

We use the Bayesian structural time series model (BSTS) to model the dynamics of each mobility signal \( U_j \) generated by WLRA. As a structural time series model, BSTS has the following additive structure.

\[
U_j(t) = \mu(t) + \tau(t) + \rho^T X + \epsilon(t),
\]

where \( U_j(t) \), the value of the \( j \)th mobility signal at time \( t \), is modeled the sum of the trend component \( \mu(t) \), the seasonal component \( \tau(t) \), the regression component \( \rho^T X \), an error term \( \epsilon(t) \sim N(0, \sigma^2) \).
Trend: The local linear trend model treats both the mean and the slope as two random walks with initial value as \(\mu(1), \delta(1)\) respectively, and

\[
\begin{align*}
\mu(t + 1) &= \mu(t) + \delta(t) + \epsilon_{\mu}(t), \\
\delta(t + 1) &= \delta(t) + \eta(t),
\end{align*}
\]

\[\epsilon_{\mu}(t) \sim \mathcal{N}(0, \sigma_\mu), \quad \eta(t) \sim \mathcal{N}(0, \sigma_\eta).\] (5)

Seasonality: The seasonality component is represented as a regression on \(S\) ”seasons” observations. Assuming the time step in each season is 1, one has

\[
\begin{align*}
t(t + 1) &= -\sum_{s=0}^{S-2} t(t-s) + \epsilon_s(t), \\
\epsilon_s(t) &\sim \mathcal{N}(0, \sigma_s).
\end{align*}
\] (6)

Regression: The third component of the structural time series model is a regression module that captures the impact of the predictor variables. In this study, we consider three types of predictors: weather (\(X_{\text{weather}}\)), COVID-19 cases and vaccination rates (\(X_{\text{COVID}}\)), and COVID-19 related policies (\(X_{\text{policy}}\)).

The Bayesian statistical method is adopted to estimate the posterior distribution of the coefficients in the above models, which gives a range for the fitting/prediction results. Moreover, the Bayesian approach also provides the inclusion probability of each predictor variable. More details of the model training can be found in Scott and Varian (2014). In this study, we use the “bsts” package implemented in R.

Model Selection

Each component in BSTS introduces a certain risk of over-fitting to the target time series, so it is important to tune the model structure and hyper-parameters properly.

For the model structure, we specifically check whether we should include a linear trend component, or just use a local level component whose slope is always zero. For the hyper-parameters, we choose the prior distribution by following the previous studies (Scott and Varian 2014; Qiu et al. 2018) which suggest using normal distributions for the variance of the trend and the seasonality components, and spike-and-slab priors for the regression components. The hyper-parameters of the prior distributions for the seasonality and the regression components are derived from the input data, which is the default setting in the “bsts” package. However, the hyperparameters of the trend component cannot be derived in the same way because the real observations always contain additional variance contributed by events like holidays and COVID-19 factors. Moreover, overestimating the trend variance can make the model treat any dynamic as the fluctuation caused by the random walk, even the sudden change during the outbreak of COVID-19. Hence, here we choose the hyper-parameters of the trend component, particularly the maximum values of \(\sigma_\mu\) (and \(\sigma_\eta\) if the linear trend is used), via cross-validation. For time series, this method is also known as forward chaining in which we divide the pre-COVID (2019) time series into 6 folds (with 180 days in the first fold and 35 days for each of the rest folds) and repetitively predict the forward-looking data using the previous folds. Then we select the combinations of the model structure and hyper-parameters with the best prediction performance measured by RMSE.

Apart from the model structure and hyper-parameters, different choices of predictor variables can influence the coefficients of the regression components in the training results. On the one hand, omitting critical variables will degrade the fitting quality, leading to a poor one-step forward prediction of the time series. On the other hand, adding unnecessary variables is unlikely to influence the fitting results, but can make the generated coefficients unstable, especially when these variables describe the same event. To select the proper set of predictor variables, we first fit BSTS models with or without three sets of predictors (\(X_{\text{weather}}, X_{\text{COVID}}, X_{\text{policy}}\)), then choose the predictor sets that can contribute significantly to the performance of the one-step-ahead prediction measured by mean absolute error (MAE) of the reconstructed ridership estimations. As such, we ensure that each set of predictors contributes significantly to the model performance. To filter out the unnecessary variables, we make use of the inclusion probability of each predictor returned by BSTS. A low inclusion probability suggests the corresponding predictor cannot effectively explain the dynamic of the target time series. In this study, we iteratively filter the predictors with the lowest inclusion probability and retrain the model so that the inclusion probability of each selected predictor in the final model is at least 50%.

Policy Indicators

We consider three potential dynamics of policy impacts. First, a policy can trigger an abrupt change of the system, e.g., the PAUSE policy in NYC caused the immediate shut down of nearly all businesses. Second, a policy may influence the trend of the system dynamics by slowly altering human behavior. Third, the end of policy may also cause an abrupt change. In light of these, we propose three types of policy indicators to encode the effect of each policy. Given the \(i\)th policy’s start date and end date are \(a_i, b_i\) \((b_i\) is set to the last day of the study period if it is not available in Table 1) respectively, we have the policy indicators defined as
For a special case, if a policy is followed by another policy, e.g., RO1 is followed by RO2 in NYC, then the earlier policy’s x_end indicator is dropped to avoid duplication. It is worth noting that the x_linear may not be sufficient to model the trendwise impacts due to the complexity of human behaviors. Here we use the linear indicators to avoid making further assumptions on policy impacts. However, with additional observable evidence, more types of policy indicators can be considered.

\[
\begin{align*}
  x_{\text{begin}}(t, i) &= \begin{cases} 
  1, & t \geq a_i, \\
  0, & \text{otherwise}; 
\end{cases} \\
  x_{\text{linear}}(t, i) &= \begin{cases} 
  1, & t \geq b_i, \\
  \frac{t-a_i}{b_i-a_i}, & a_i \leq t \leq b_i, \\
  0, & \text{otherwise}; 
\end{cases} \\
  x_{\text{end}}(t, i) &= \begin{cases} 
  1, & t > b_i, \\
  0, & \text{otherwise}. 
\end{cases}
\end{align*}
\] (7)

Results

Importance of Different Factors

This section shows results on the importance of different factors in the model selection process. The full model selection results can be found in the appendix.

Figure 3A shows the cumulative one-step-ahead MAE of the reconstructed ridership by BSTS with different choices of predictors. A striking feature of this figure is that the jump of the cumulative MAE during the outbreak of COVID-19 is flattened after introducing the COVID-19 related factors (X_COVID and X_policy), which in turn reflects the value of including these predictors. In addition, we also observe that including X_weather results in a smaller one-step-forward cumulative MAE for BSS ridership, and the models without X_weather generate another jump when the temperature starts to decrease in September 2019. These confirm that
the usage of BSS is sensitive to weather-related factors. In general, including any set of factors can significantly reduce the cumulative MAE for at least one travel mode, and the models with COVID-19 related predictors accumulate the error at a slower rate than the models without these factors. Hence, we select all sets of factors in this step.

We then plot the posterior inclusion probabilities of different factors in the selected model in Fig. 3B, where the green squares highlight the factors used in the final models. Note that the importance of a mobility signal decreases as its index increases. For both cities, the log(RAIN) is preferred over the plain RAIN factor. The number of cases (CASE) is not selected in modeling most mobility signals, except the first mobility signal in Chicago. The vaccination rate (VAC) plays a significant role in modeling a few mobility signals.

Most policies play a significant role in describing at least one mobility signal, except RO1 (reopening of constructions, manufactures, wholesalers, outdoor businesses, and food delivery) and RO3 (indoor personal care and “low-risk” sports) in NYC. This result indicates the trend of OMS ridership did not experience significant change during the effective period of RO1 and RO3, which suggests these policies do not have significant influence on the recovery process of OMS. The policies deployed during the first outbreak, like PH1 (state of emergency) and MR1 (stay-at-home), exhibit instant impact to the first mobility signal for both cities and the second mobility signal for NYC. Following these early policies, PH2 (mandatory masking) and the RO (reopening) policies tend to show slower effects. For Chicago, we also observe that the business restrictions introduced during the end of 2020 (BR2) brings instant impacts on the second most important mobility signal. This result is expected as the BR2 policy is targeting all non-essential business in Chicago.

### Influence of Different Factors

After selecting predictors, we examine the aggregate influences of different factors. As shown in Fig. 4, each box represents the distributions of daily usage of OMS correlated...
by different factors. The first column shows the daily average impacts of the factors belonging to $X_{\text{weather}}$ and $X_{\text{COVID}}$. The values in the brackets show the numbers of days correlated to the corresponding factors. First, some intuitive relationships can be observed: rainy weather is a negative factor and temperature serves as a strongly positive factor to the usage of BSS. For the COVID-19 cases and vaccination rates, we observe that the number of cases (CASE) shows negative influence on the ridership of all the OMS modes in Chicago. The vaccination rate (VAC) is correlated to the decrease of FHV ridership and the increase of BSS usage, but VAC does not explain much about the change of the total ridership in Chicago.

The second column shows the instant impacts of different COVID-19 related policies. It can be observed that some policies, including the declaration of a state of the emergency (PH1) and the lockdown in early 2020 (MR1), instantly reduce the trips by 20–50%. In Chicago, we also observe that the business curfew (BR2) has an instant negative shock to BSS usage, and the end of the liquor sales curfew (BR1) shows a positive influence to the BSS usage.

The last column shows the daily change of policy effects and the bracketed values shows the lasting days of the corresponding trends. It can be observed that mandatory masking contributes to the most significant and long-lasting recovery of all three modes. The reopening (RO) policies exhibit different influences for different modes. In NYC, the second recovery policy (RO2) is correlated to the increase of FHV ridership and the decrease of bikesharing trips. In Chicago, the first recovery policy is negatively correlated with the taxi ridership, but contributes positively to the increase of bikesharing trips. Both the mobility restrictive and business restrictive policies applied in late 2020 (MR3 in NYC and BR2 in Chicago) show a negative impact on the recovery speed.

In general, we observe that (the logarithm of) the COVID-19 cases, the first public health, and mobility restrictive policies play an essential role in the plunge of the OMS ridership, while the mandatory masking (PH2) and reopening policies (RO) contribute to the recovery trend of daily trips.

### One-Year Prediction of Recovery Process

We conduct a one-year prediction of daily ridership of OMS from August 1, 2021, to July 31, 2022, under two scenarios. In the first scenario, there is no additional policy in the prediction period; in the second one, there are the same policies introduced after July 1, 2020. In addition, we assume the weather factors are repeating with the values from August 1, 2020, to July 31, 2021, and the number of COVID-19 cases stabilized to the same level in July 2021 and the vaccination rates are unchanged since July 31, 2021. The prediction results, and the ground truth until December 2021 are visualized in Fig. 5. The real values after July, 2021 come from the monthly report in NYC and an online dashboard for Chicago.

From Fig. 5, it can be observed that the predicted mean of the ridership under the second scenario fits well with the real values reported in other sources. In most cases, the percent

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9 See https://www1.nyc.gov/site/tlc/about/aggregated-reports.page.
10 See https://toddwschneider.com/dashboards/chicago-taxi-ridehailing-data/.
deviation of the predicted values to the true ones are within 20%. Moreover, the trends and turning points reflected in the ground truth data can be also found in the prediction results. We notice that the prediction results for FHV in September abruptly deviates from the ground truth in both NYC and Chicago. This is likely due to the impact of the Delta variant, a highly contagious variant which contributed to 98% of total cases in NYC for the last four weeks of September based on the NYC coronavirus data repository.11 Nevertheless, the prediction result for October and November align very well with the ground truth, which suggests the shock potentially caused by the Delta variant does not change the long-term recovery trend. For the BSS usage, the prediction performances in November are significantly worse than previous months in both cities; this is because the temperature in November 2020 is the warmest on record (on average 5 degrees greater than its normal value) and we assume the weather factors in November 2021 are similar to November 2020.

For the longer time period, the mean of the prediction that the FHV and taxi are likely to recover slowly, and the recovery speed in NYC is faster than the rate in Chicago. In the scenario without any new restrictive policy, the recovery ratio of FHV and taxis will reach 120% in NYC, and 80–100% in Chicago. With additional restrictive policies, the ridership of FHV will fluctuate around the pre-COVID value in NYC, and 80–90% in Chicago. The recovery ratio of taxi trips is around 70–80% in NYC, and 30–40% in Chicago. Unlike the FHV and taxi, the result suggests that the usage of BSS in NYC and Chicago would just experience a slight increase in 2022 without any restrictive policy, or a slight decrease in NYC but an increase in Chicago with additional restrictive policies. Figure 5 also shows the 95% confidence intervals of the prediction values. We report that the confidence interval is large for FHV and taxis, suggesting a more uncertain future about the usage of these modes.

11 See https://github.com/nychealth/coronavirus-data/blob/2bf6b3e1694ed12f35f54980c666f51fbc578052/variants/variant-classification.csv.
Correlation Between Spatial Distribution of OMS Trips and Different Factors

Besides the total number, different factors can also influence the spatial distribution of the OMS ridership. In this section, we investigate such impacts and summarize the key results in Fig. 6. One can refer to the appendix to see the full visualization of the spatial distribution of correlated trips under different factors.

Figure 6A shows the distribution of correlated trips under four (two for each city) selected policies. One can observe that the correlated ridership is different across the city. For downtown (CBD shown in Fig. 2B), we observe that PH1 (state of emergency) is accompanied by a decreasing trend of FHV and taxi ridership, but a increasing trend of BSS usage; BR1 (liquor sales curfew) is accompanied by increasing ridership for FHV, decreasing ridership for taxi, and decreasing usage of BSS. For the communities surrounding CBD, positively correlated ridership can be observed for all three modes under PH1 and BR1. Interestingly, RO4 and RO2 introduced almost opposite dynamics to PH1 and BR1 respectively. We observe that the ridership in CBD and airports is increasing for NYC, and it is decreasing for the other part of the city.

To further explore the difference between the different regions of the city, we present the correlated ridership aggregated by regions under different factors. As shown in Fig. 6B, the state of emergency (PH1), mobility restrictions (MR), and the non-essential business curfew in Chicago (BR2) are correlated to ridership decreasing in all regions, while the reopening policies (RO) often correlate with different directions of ridership change in different regions. These suggest the recovery speed of OMS ridership is heterogeneous in different regions of the city and there exists complicated interactions between OMS usage and reopening policies, which may require additional attention from transportation agencies when reopening their services.

Figure 6C shows the cosine similarity of correlated ridership for different modes. We report that most policies in NYC show consistent influence to different OMS modes except the trend accompanied with PH1 and MR1, while in Chicago, some policies, including BR1, RO2 show contrast influences to FHV and taxi, and RO1 and BR1 show opposite influence to FHV and BSS usage.

Related work

COVID-19 Impact to Human Mobility

There has been significant recent work in investigating the change of mobility patterns during COVID-19. Table 2 summarizes the data-driven studies for understanding the COVID-19 impact to OMS. It can be observed that most studies are dedicated to bikesharing systems, while the ride-hailing systems are relatively less investigated. Two types of mobility data are mainly used: the highly aggregated data, like the Google/Apple’s mobility trend reports, are used to understand the overall change of the mobility activities, trip purposes, and mode splits during the pandemic; the disaggregated data, like the trip records collected by transportation service providers, are employed to unveil the heterogeneity of different communities in term of the reactions to the COVID-19 and its related events.

The most salient finding of these studies was the dramatic decrease in mobility activities. The sudden drop in the mobility activities were widely reported in the early studies (Bucsky 2020; Batool et al. 2020). Later studies confirmed the existence of such phenomena and pointed out the slow recovery of urban mobility services, including mass public transit, street-hailing, and ride-hailing (Bus and Ferreira 2021; Wang et al. 2021; Zheng et al. 2021), except bikesharing (Kubal’á et al. 2021; Padmanabhan et al. 2021). The second finding was the heterogeneity of mobility changes for communities with different socio-economic features. For example, Hu et al. found that the bikesharing usage in Chicago was correlated to the region’s income, race, and educational level (Hu et al. 2021). Thirdly, the trip duration and travel distance of bikesharing were found to significantly increase (Teixeira and Lopes 2020; Padmanabhan et al. 2021; Wang et al. 2021). Last but not the least, the researchers also investigated the alternative effects among different transport modes during the COVID-19: the bikesharing services could substitute public transport (Li et al. 2020), while the overlapping coverage of ridehailing and public transit decreased (Meredith-Karam 2021). It is worth noting the last three findings are mainly provide an aggregate view of these systems, and do not describe the temporal dynamics.

Besides the analyses based on mobility records, survey-based work also plays an important role in understanding how the COVID-19 pandemic could reshape the future of OMS. It was widely reported that people’s opinion of different mobility choices has changed due to the pandemic (Nikiforidis et al. 2020; Awad-Núñez et al. 2021; Bhaduri et al. 2020; Shamshiripour et al. 2020; Rasheed Gaber and Elsamadicy 2021; Loa et al. 2022). For instance, the general willingness to use bikesharing services was unchanged (Nikiforidis et al. 2020) or became higher (Awad-Núñez et al. 2021) than the pre-COVID period. People would stop using the ridehailing and public transit services due to the risks of human-to-human contact (Bhaduri et al. 2020; Shokohyar et al. 2021; Rasheed Gaber and Elsamadicy 2021; Loa et al. 2022) and telecommuting was likely to continue and thus reduce the travel demand (Shamshiripour et al. 2020).
However, under the combination of these influences, the future of urban mobility is highly uncertain. Only a few studies explored the impact of COVID-19 policies on urban mobility. Armstrong et al. (2020) investigated the mobility patterns and policy environments in 75 Canadian and American cities using Apple’s Mobility Trends Reports; they found that increases in policy aggressiveness led to large decreases in transit. Praharaj et al. (2020) compared Apple’s mobility trends during three lockdown phases in Sydney, London, Phoenix, Pune; they reported that the consistent significance of mobility drop between Phase 1 and Phase 2, and the varied significance of mobility recovery between Phase 2 and Phase 3. Bian et al. (2021) estimated the length of the policy lag and the magnitude of policy impact in New York City and Seattle by modeling the corresponding change points of the trip numbers of different traffic modes; they found that policy lag and magnitude of impact are varied in Seattle and NYC despite having a very similar vehicular traffic trend.

### Table 2: List of data-driven studies on COVID-19 impact to on-demand mobility systems

| Subject               | Study                                      | Date of publication | Study region                | Data                                                                 | Method                                               |
|-----------------------|--------------------------------------------|---------------------|-----------------------------|----------------------------------------------------------------------|-------------------------------------------------------|
| Mode share            | Bucsky (2020)                              | Jun-20              | Budapest, Hungary           | Road traffic, Waze, Google’s mobility report, BSS, and survey data.  | Descriptive analysis                                  |
| Mode share            | Basu and Ferreira (2021)                   | Feb-21              | Metro Boston                | Transit app data, census data, household survey data                  | Descriptive analysis                                  |
| Sharing economy       | Batool et al. (2020)                       | Sep-20              | Nine selected countries     | Google search trends                                                 | Difference-in-difference                             |
| Micro-mobility        | Li et al. (2020)                           | Aug-20              | Zurich, Switzerland         | Trip data, GPS survey data                                           | Rule-based activity imputation                        |
| Bikesharing           | Teixeira and Lopes (2020)                  | Jul-20              | New York City               | Bikesharing data, subway rides data                                  | Descriptive analysis, Ordinary least square regression|
| Bikesharing           | Pase et al. (2020)                         | Oct-20              | New York City               | Bikesharing data, subway rides data                                  | Descriptive analysis, graph theory                    |
| Bikesharing           | Padmanabhan et al. (2021)                  | Dec-20              | New York City, Boston, and Chicago | Bikesharing data                                                       | Ordinary linear regression                           |
| Bikesharing           | Shang et al. (2021)                        | Jan-21              | Beijing, China              | Bikesharing data                                                       | Descriptive analysis, Complex network theory          |
| Bikesharing           | Hu et al. (2021)                           | Feb-21              | Chicago                     | Bikesharing data, census data                                        | Generalized additive model                           |
| Bikesharing           | Kubal’áč et al. (2021)                     | Jun-21              | Kosice, Slovakia            | Bikesharing data                                                       | Descriptive analysis                                  |
| Bikesharing           | Kim (2021)                                 | Aug-21              | Seoul, Korean               | Bikesharing data, weather data, POI location data, census data        | Negative binomial regression                          |
| Street-hailing        | Nian et al. (2020)                         | Sep-20              | Chongqing, China            | Taxi trip data, POI data                                              | Spatial regression                                    |
| Street-hailing        | Zheng et al. (2021)                        | Jun-21              | Shenzhen, China             | Taxi trajectory data                                                  | Descriptive analysis                                  |
| Ridehailing           | Morshed et al. (2021)                      | May-21              | Florida                     | Tweeter data, state-preference survey data                           | Sentiment-Emotion Detection model                     |
| Ridehailing and public transit | Meredith-Karam (2021) | Sep-21 | Chicago | Ridehailing and transit trip data, transit schedule data, census data | Spatial regression                                    |
| Ridehailing           | Zwick et al. (2021)                        | Oct-21              | Hamburg, German             | Ridehailing trip data, facility location data                         | Spatial regression                                    |

In the data column, we omitted the COVID-19 data because it was used in all these studies.
Applications of Bayesian Structural Time Series Model

Bayesian structural time series model (BSTS) has seen wide applications in different fields including public health (Feroze 2020), weather forecasting (Jiang et al. 2013), social media (Welbers and Ogenhaff 2018), disaster resilience (Yabe et al. 2020b), stock market (Jammalamadaka et al. 2019), and climate change (Rohmer and Le Cozannet 2019). In general, BSTS can be used in time series prediction, feature selection and causal impact inference (Scott and Varian 2014; Brodersen et al. 2015; Jammalamadaka et al. 2019).

Some studies have performed COVID-19 versus mobility analysis using BSTS. Hu and Chen (2021) used BSTS to infer the causal impact of the COVID-19 on transit ridership in Chicago. Zhang and Fricker (2021) adopted BSTS to estimate the changes of non-motorized trips caused by COVID-19 in 11 cities in the United States. Our work is different from these studies as we focus on the prediction and the feature selection instead of the estimation of causal impact.

One limitation of BSTS is that it does not support multivariate time series. Although there is a multivariate extension of BSTS called MBSTS (Qiu et al. 2018), it does not scale well for high-dimensional target time series due to the quadratic increase of the number of model parameters (covariance terms) to the number of dimensions. Thus, additional methods are needed to effectively utilize the correlation between different target time series.

Conclusion and discussion

In this study, we investigate the correlation between the COVID-19 related factors (i.e., policies, number of cases, and vaccination rates) and the ridership dynamics of on-demand mobility services (OMS) using two and a half year data (January 2019 to July 2021) collected from NYC and Chicago. By fitting the low-rank representations of community-level daily OMS ridership with COVID-19 related factors using BSTS, a highly explainable time series model, we quantify the potential impacts of different factors in these cities and provide the one-year predictions for future recovery processes. The model is validated by (1) its smooth and relatively small cumulative one-step-forward prediction error and (2) the good predicted recovery levels (from August 2021 to December 2021) that align with the real observations from aggregated reports.

This is the first study to uncover the correlation between the OMS usage and COVID-19 related factors. It contributes to a better understanding of the spatio-temporal impact of COVID-19 on the usage of OMS with the following findings and implications for policies and practices.

Response of OMS Ridership to Different Factors

Different factors affect the OMS ridership with varying extents and speeds. Among these factors, the early public health interventions, e.g. the declaration of a state of emergency (PH1), the stay-at-home policy (MR1) show the most salient immediate impact on the usage of OMS. The later policies mainly influence the trend of the ridership dynamics. For each city, we find the mask mandate is closely correlated with a significant recovery trend of the ridership of all studied modes in all communities. The potential reason for this is that the mandatory mask can provide a sense of safety and therefore help restore the mobility activities. An alternative explanation is the “lockdown fatigue”, which suggests over time people are becoming less willing to comply with the mobility restrictions. More evidence needs to be collected to distinguish these two reasons. The reopening (RO) policies do not always result in a faster recovery speed of the OMS ridership. Instead, they influence different travel modes and different regions in different ways.

In general, we find the restrictive policies can trigger fast and consistent decreases of OMS ridership across the entire city; however, the ridership would not quickly bounce back after these restrictions are lifted. The recovery speed is heterogeneous for different regions of the city under different policies. For policymakers, it is important to take account of the loss of mobility activities, and the heterogeneous recovery speed to have a better plan for the restriction and reopening policies. For the operators of OMS platforms, such circumstance introduces additional challenges to plan for expanding the supply, which create a need for hedging against uncertain policy environment (e.g., via promoting food delivery).

The “New Normal”

As the pandemic has radically altered the mobility patterns, adapting to the “new normal” is a crucial challenge in the aftermath of COVID-19. Our analyses indicate that the OMS ridership is still evolving during the studied period, and is unlikely to become stable within the first half of 2022 even without additional policies and the new wave of COVID-19 cases. In other words, the “new normal” has not been settled and is unlikely to be settled within the first half of 2022. Comparing the prediction results for the second half of 2021 with the ground truth gathered from the aggregated reports, we find that the recovery process is likely to follow the hypothetical scenario if the same restrictive policies

See https://assets.researchsquare.com/files/rs-621368/v1_covered.pdf?c=1631870787.

See https://arxiv.org/ftp/arxiv/papers/2009/2009.14018.pdf.
in winter 2020 are introduced again in 2021. In addition, we find that the FHV ridership shows a jump in September 2021, which may be due to the shock of the Delta variant. For the first half of 2022, our prediction suggests that the trip demands for FHV and taxis in both cities would not be fully recovered, except for the FHV ridership in NYC. The demand for BSS will reach two to three folds of the level in 2019, and we expect to see the demand becomes stable with the fluctuations caused by different weather conditions.

The above findings suggest that for a considerable period, the OMS providers will face variable ridership, which can place new challenges on system operations. Some operational techniques which relies on stable system dynamics, like the reinforcement learning based vehicle dispatching (Qin et al. 2020b) and the prediction based BSS fleet rebalancing (Hulot et al. 2018) may obtain inferior performances because of the evolving demand patterns. To tackle this challenge, it would be important to understand how the changes of demand patterns would affect the operational efficiency.

**Replacement Between Bikesharing and Other Modes**

Although no definite conclusion can be drawn about the final recovery rate of FHV and taxis in the “new normal” stage, enough evidence has shown that the demand for BSS would increase by more than 100% compared with 2019 levels. In addition, we observe that the recovery speeds for the usage of bikesharing and other modes can change in opposite directions for some policies, which suggest there exist certain replacements between BSS and other modes in both cities. For NYC, the declaration of the state of emergency (PH1) triggers an increasing trend of BSS usage in CBD and its surrounding communities, but a decreasing trend of FHV and taxi ridership in CBD. Similar trends can also be observed in Chicago. This is because the current BSS stations are mainly distributed in these communities, and bikes can serve as a good alternative option to taxis/FHV. Moreover, we also find the increasing speed of BSS trips outside the CBD declines as more restrictions are lifted (RO4 in NYC and RO2 in Chicago), which suggests that BSS becomes less attractive in peripheral regions as other modes recover.

These findings have a two-fold implication. First, it is important to provide enough facilities to meet the increasing demand for BSS in various locations. Second, as the usage of BSS is strongly influenced by weather conditions, the ridership of the modes replaced by BSS can exhibit stronger seasonal fluctuations than in the pre-COVID-19 period, which can add some challenges in deciding the system capacity.

**Similarity Between Different Cities**

Despite NYC and Chicago are with different populations and sizes of OMS markets, we still find similar recovery processes of OMS ridership. For example, certain types of COVID-19 related policies (e.g., PH and RO) show consistent spatiotemporal correlation with the OMS ridership in these cities. This suggests the existence of the transferable knowledge about the influence of COVID-19 related policies and the recovery of the urban mobility system. As different cities may experience different stages of the pandemic, the finding from the city in a later stage may guide the policy decisions of the city in earlier stages.

For future study, we should include additional data with more modes and factors, e.g., the demand of food delivery and the number of active drivers, to get a more comprehensive picture of the underlying recovery mechanism. The aggregated indexes of such factors can be found in industry reports such as Google’s community mobility reports and Apple’s mobility trends reports, while the disaggregated values with richer spatial information may be available to local governors and service providers. Second, we should also understand the connection between the ridership change and the operational efficiency. The later can be measured by the ratio of the cruising/rebalancing trip time estimated from the trip records. Third, more types of policy indicators can be considered with the specific observable evidence. For example, the odd-even system of traffic rules (Li and Guo 2016) may create periodic effects, which needs recurrent policy indicators. Finally, using the same framework to investigate the impact of other events or policies is also a promising direction. The target time series can be replaced by any multivariate observations, such as the daily number of trips by modes/purposes/origins/destinations, daily business transactions by regions, or the traffic condition measured by average speeds of different links. The predictors can be the sets of available covariates that are believed to have a causal relationship with the target like the introduction of new products/policies/technologies. Then our framework can be applied to analyze the spatiotemporal correlation and hopefully shed some light on the causality between the target time series and predictions.

**Appendix A: Result of Weighted Low-Rank Approximation (WLRA)**

Following the process described in “Weighted low rank approximation for multivariate time series”, we perform WLRA to aggregate the multi-variate ridership observations into multiple mobility signals. The results of WLRA is shown in Fig. 7. Figure 7A shows the reconstruction quality, measured by MSE and MAE, with respect to different
choices of the number of signals $K$. It can be observed that a few signals can capture the most of dynamics of the travel patterns. The reconstruction error is smaller than 10% for every mode. Moreover, when comparing the elementwise difference between the original data and the reconstructive one, we report that they nearly fall on the diagonal line, as shown in Fig. 7B. Figure 7C shows the relative value of different mobility signals. Interestingly, the first three mobility signals in Chicago and NYC are similar, which suggests the existence of some common patterns.

**Table 3** Cross-validation results for trend components in NYC

| Signal | Local Level | Linear trend | RMSE | $\sigma_{\mu}/sd(y)$ | $\sigma_{\mu}/sd(y)$ | $\sigma_{\nu}/sd(y)$ | $\sigma_{\nu}/sd(y)$ | RMSE |
|--------|-------------|--------------|------|----------------------|----------------------|----------------------|----------------------|------|
| 1      | 6.10E−05    | 9.38826      | 9.54E−07 | 1.53E−05            | 10.11738             |
| 2      | 0.003906    | 10.69684     | 0.003906 | 1.53E−05            | 9.892344             |
| 3      | 0.000977    | 11.66265     | 0.000977 | 3.81E−06            | 11.37498             |
| 4      | 0.003906    | 10.92896     | 0.003906 | 9.54E−07            | 11.54348             |
| 5      | 1.53E−05    | 20.45999     | 0.000977 | 1.53E−05            | 20.59351             |
| 6      | 0.003906    | 23.04872     | 0.003906 | 1.53E−05            | 16.00242             |
| 7      | 0.000244    | 15.48548     | 0.000244 | 9.54E−07            | 16.79111             |
| 8      | 0.000977    | 7.30005      | 0.000977 | 9.54E−07            | 7.02486              |
| 9      | 0.003906    | 12.87469     | 0.003906 | 1.53E−05            | 12.82494             |
| 10     | 6.10E−05    | 14.10018     | 0.000977 | 1.53E−05            | 11.35611             |

**Table 4** Cross-validation results for trend components in Chicago

| Signal | Local Level | Linear trend | RMSE | $\sigma_{\mu}/sd(y)$ | $\sigma_{\mu}/sd(y)$ | $\sigma_{\nu}/sd(y)$ | $\sigma_{\nu}/sd(y)$ | RMSE |
|--------|-------------|--------------|------|----------------------|----------------------|----------------------|----------------------|------|
| 1      | 0.003906    | 9.080876     | 9.54E−07 | 1.53E−05            | 10.11738             |
| 2      | 0.000244    | 9.567941     | 6.10E−05 | 9.54E−07            | 8.251952             |
| 3      | 0.000977    | 7.30005      | 0.000977 | 9.54E−07            | 7.02486              |
| 4      | 0.003906    | 12.22911     | 0.003906 | 9.54E−07            | 11.54348             |
| 5      | 0.003906    | 16.76823     | 0.000977 | 9.54E−07            | 16.7923              |
| 6      | 0.000244    | 13.0986      | 0.000244 | 9.54E−07            | 14.31097             |
| 7      | 0.003906    | 9.212466     | 0.003906 | 1.53E−05            | 10.83147             |
| 8      | 0.003906    | 8.672314     | 0.003906 | 9.54E−07            | 8.707948             |
| 9      | 0.003906    | 12.87469     | 0.000244 | 3.81E−06            | 11.26817             |
| 10     | 0.003906    | 10.95912     | 0.000244 | 3.81E−06            | 10.09525             |

**Appendix B: Model Selection**

**B.1 Selection of Trend Component**

We tune the upper limit of the $\sigma_{\mu}$ and $\sigma_{\nu}$ to make sure the trend component only captures the long-term dynamics. We decide the proper choice by running a 5-fold cross validation using data in 2019. The $\sigma_{\mu}$ is selected from $4^{-i}, i = 4, 5, 6, 7, 8, 9, 10$. The $\sigma_{\nu}$ is selected from $4^{-i}, i = 8, 9, 10$. Note we intentionally avoid choosing large values of $\sigma_{\mu}$ and $\sigma_{\nu}$ as they will cause the model to overfit the time series and treat the sudden change caused by COVID-19 as a normal fluctuation. The choice of the model parameters are reported in Tables 3 and 4, where $sd(y)$ is the...
standard deviation of the values of the corresponding mobility signal in 2019. The bold values show the best performance among all combinations of the candidate parameters. It can be observed that for the first mobility signal, the model without linear trend is preferred, while the second and the third signals contain linear trends.

### B.2 Selection of predictors

This section shows the models’ fitting performances, quantified by the total one-step-forward prediction MAE, under different choices of predictors. Furthermore, we also test the case of using the logarithm of ridership as the modeling targets, which can be taken as modeling the changing rate instead of the absolute value of the ridership. As shown in Table 5, it can be observed that the model achieve the best performance (marked in bold) when using all predictors or just including $X_{\text{weather}}$ and $X_{\text{policy}}$, and using the absolute value of the ridership can result in a better performance. We also note that when there is no predictor, or are just irrelevant predictors, using logarithm can help the model achieve a smaller cumulative MAE. This is expected because the changing rate is more stable, and therefore easier to be fitted by the trend component than the absolute value. Based on these results, we use the absolute numbers of ridership as the modeling targets and include all predictors for deriving the final model.

### Appendix C: Spatial Distribution of the Correlated Trips

We plot the spatial influences of all factors with significant number of influenced trips (> 5% of daily ridership in 2019 for at least one mode) in Figs. 8 and 9. It can be seen that the early policies (PH1 and MR1) hugely reduce mobility activities. Note in Fig. 4 we have seen that both of them contribute similarly to the total ridership, here we find that they have distinct spatial impacts: the PH1 (state of emergency) policy reduces the ridership in the city centers with high population density, while the MR1 (stay-at-home) policy reduces the ridership across the entire city. Following these two policies, the PH2 (the mandatory masking) cancels out most of the impacts of the PH1 and MR1. In NYC, MR2, the one-week mobility curfew in downtown Manhattan, reduces the usage of BSS in that region but plays a positive role in the ridership of FHV. MR3, the cluster zone restriction also reduces the ridership across the city. In Chicago, we report that MR2, the advisory stay-at-home policy, slightly reduces the ridership.

Figures 8 and 9 also suggest certain replacements between different modes. As for NYC, we observe that PH1 reduces the ridership of FHV in Manhattan midtown while increasing the ridership of FHV in the same area. Interestingly, RO2 seems to reverse this trend, as the ridership of FHV increases while the usage of BSS decreases in Manhattan midtown. In Chicago, we report a similar phenomenon, like the MR2 triggers the replacement of FHV with bikesharing in the zone near the city center. However, unlike NYC, the

### Table 5: Cumulative (weighted) MAE under different settings

|                    | NYC |   |   |   |   | Chicago |   |   |   |   |
|--------------------|-----|---|---|---|---|---------|---|---|---|---|
| $y(t)$             |     |   |   |   |   |         |   |   |   |   |
| No predictor       | 319.6 | 416.3 | 1012.8 | 345.0 | 456.7 | 1024.0 |   |   |   |   |
| $X_{\text{weather}}$ | 319.7 | 415.4 | 836.1 | 330.3 | 461.3 | 602.7 |   |   |   |   |
| $X_{\text{COVID}}$ | 245.6 | 336.2 | 777.0 | 280.4 | 394.8 | 909.8 |   |   |   |   |
| $X_{\text{policy}}$ | 105.7 | 128.5 | 595.1 | 144.0 | 195.8 | 662.9 |   |   |   |   |
| $X_{\text{weather}} + X_{\text{COVID}}$ | 227.1 | 310.4 | 633.0 | 270.8 | 393.6 | 542.6 |   |   |   |   |
| $X_{\text{weather}} + X_{\text{policy}}$ | 104.7 | 127.1 | 579.5 | 141.2 | 198.0 | 644.4 |   |   |   |   |
| All predictors     | 100.0 | 119.6 | 413.5 | 118.6 | 187.2 | 430.3 |   |   |   |   |
| $\log(y(t) + 1)$   |     |   |   |   |   |         |   |   |   |   |
| No predictor       | 225.6 | 294.8 | 927.8 | 425.3 | 455.2 | 941.1 |   |   |   |   |
| $X_{\text{weather}}$ | 224.6 | 278.0 | 715.1 | 242.5 | 273.0 | 551.6 |   |   |   |   |
| $X_{\text{COVID}}$ | 200.6 | 243.2 | 662.1 | 398.5 | 419.5 | 806.5 |   |   |   |   |
| $X_{\text{policy}}$ | 136.0 | 174.8 | 650.3 | 340.6 | 368.0 | 706.6 |   |   |   |   |
| $X_{\text{weather}} + X_{\text{COVID}}$ | 191.2 | 292.3 | 576.9 | 210.1 | 268.8 | 527.3 |   |   |   |   |
| $X_{\text{weather}} + X_{\text{policy}}$ | 111.2 | 145.2 | 464.3 | 141.8 | 188.3 | 481.5 |   |   |   |   |
| $X_{\text{COVID}} + X_{\text{policy}}$ | 126.1 | 167.6 | 631.8 | 336.3 | 366.2 | 598.5 |   |   |   |   |
| All predictors     | 115.3 | 146.7 | 463.7 | 141.1 | 186.1 | 481.0 |   |   |   |   |
trend of replacement is reinforced under reopening policies (RO1, RO2).

Figures 8 and 9 also separately present the impacts on the pickup and drop-off trips. It can be observed that the pickup and drop-off changes are almost identical for each zone, except for the airport. Some policies, including RO2, BR1 in NYC, and RO2 in Chicago, may induce more drop-off trips than pickup trips in the corresponding airport zone.

Fig. 8 Spatial distribution of correlated trips in NYC
Fig. 9 Spatial distribution of correlated trips in Chicago

The ridership in peripheral regions follows a different trend to the communities in CBD under events like RO1, RO3. The influences to the pickup and drop-off are nearly identical, except for the airports, where the policies exhibit more influence to the pickup rides. Certain replacements between BSS and other modes are identified in the places surrounding CBD, as shown in the plots of PH1, RO2.
Declarations

Conflict of Interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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