Examining spatiotemporal changing patterns of bike-sharing usage during COVID-19 pandemic

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A B S T R A C T

The COVID-19 pandemic has led to a globally unprecedented change in human mobility. Leveraging two-year bike-sharing trips from the largest bike-sharing program in Chicago, this study examines the spatiotemporal evolution of bike-sharing usage across the pandemic and compares it with other modes of transport. A set of generalized additive (mixed) models are fitted to identify relationships and delineate nonlinear temporal interactions between station-level daily bike-sharing usage and various independent variables including socio-demographics, land use, transportation features, station characteristics, and COVID-19 infections. Results show: 1) the proportion of commuting trips is substantially lower during the pandemic; 2) the trend of bike-sharing usage follows an "increase-decrease-rebound" pattern; 3) bike-sharing presents as a more resilient option compared with transit, driving, and walking; 4) regions with more white, Asian, and fewer African-American residents are found to become less dependent on bike-sharing; 5) open space and residential areas exhibit less decrease and earlier start-to-recover time; 6) stations near the city center, with more docks, or located in high-income areas go from more increase before the pandemic to more decrease during the pandemic. Findings provide a timely understanding of bike-sharing usage changes and offer suggestions on how different stakeholders should respond to this unprecedented crisis.

1. Introduction

Starting from late 2019, the novel Coronavirus disease 2019 (COVID-19) pandemic has spread rapidly across the world, deteriorating into one of the worst global health crises seen in decades. As of November 3rd, 2020, the number of confirmed cases in the U.S. has surpassed over 9.34 million, with the death toll surpassing 33,500 (CSSE, 2020). The outbreak of COVID-19 has posed unprecedented challenges for the government. Aside from medical measures, non-pharmaceutical interventions like stay-at-home orders to restrict human movement have been widely adopted across the nation to contain the virus's spread (Xiong et al., 2020b). In the U.S., stay-at-home orders were instituted across all but eight states by mid-April 2020, indicating at least 316 million people were being urged to stay home, reduce unnecessary contact, and keep social distancing.

Non-pharmaceutical interventions and the virus itself triggered dramatic changes in human mobility patterns, no matter walking,

cycling, riding transit, driving alone, or carpooling. Although several studies have already reported the globally unprecedented decline in human movement (Bliss et al., 2020), rare studies have solely focused on cycling changes. Examining the change in cycling during the pandemic is in imperative need for several reasons. First, cycling is considered a more efficient and safer travel option to maintain social distancing during the epidemic, especially compared with riding transit and carpooling in crowded spaces and public environments. Therefore, individuals may shift from those high-risk modes to cycling to minimize the risk of infection (Nikiforiadis et al., 2020), leading to spatiotemporal cycling demand changes compared with regular periods (Bucsky, 2020). To better manage the supply-demand balance and effectively provide cycling services, local governments and cycling service providers should consider such changes in advance and rejudge the post-pandemic niches of cycling. Second, cycling's socio-economic disparities have attracted various researchers' attention for a long time (Campbell and Brakewood, 2017; Caspi and Noland, 2019). For example, whether high-income

groups or low-income groups cycle more gained controversial opinions in prior studies (Caspi and Noland, 2019; Wang and Lindsey, 2019). During the pandemic, several reports have claimed that human mobility drops considerably less among uneducated, low-income, and people of color communities (Bliss et al., 2020; Brough et al., 2020; De Vos, 2020; Hu et al., 2021; Sy et al., 2020; Wilbur et al., 2020), suggesting the cycling's socio-economic disparities may also exist or even polarize during the pandemic. The difference in bike-sharing usage among areas with different socio-economic backgrounds is worth exploring and can unveil inequalities in the impact of the pandemic on different population groups.

Bike-sharing has been widely considered as a reliable source to study travel behavior regarding cycling. Information on cycling trips using private bikes are hard to collect; on the contrary, due to the General Bikeshare Feed Specification (GBFS), most dock-based bike-sharing systems in U.S. cities have made their transaction data available to the public. Moreover, bike-sharing systems have expanded rapidly over recent years and cover most of the population in many major cities, eliminating small-sample selection biases when studying cycling behavior. This study intends to examine the changes in cycling during the pandemic using the biggest bike-sharing program named Divvy in the city of Chicago as a case. Several research questions are proposed:

1) How do the bike-sharing usage change spatiotemporally during the pandemic?
2) Is bike-sharing a more resilient option compared with other modes of transport like driving, transit, and walking?
3) What are the underlying disparities in the impact of COVID-19 on bike-sharing usage across regions with different land use, socio-economic features, transportation facilities, station characteristics, and COVID-19 infections?
4) What are the nonlinear interactions between time and other regional components regarding bike-sharing usage? Namely, how do the relationships established in 3) vary across the pandemic?

To answer these questions, station-level average daily pickups and cumulative relative changes were analyzed. A detailed descriptive analysis was first conducted to document the spatiotemporal usage patterns of shared bikes. A comparison among different modes of transport including driving, transit, bike-sharing, and walking regarding their temporal evolution across the pandemic was also performed. Subsequently, three generalized additive models (GAMs) were employed to conduct cross-sectional analysis, using the regular (the year of 2019) average bike-sharing usage, the pandemic (the year of 2020) average bike-sharing usage, and the cumulative relative bike-sharing usage change (i.e., 2020 versus 2019) as dependent variables, respectively. Finally, controlling for weather conditions, time-series seasonality, and holiday effects, a set of generalized additive mixed models (GAMMs) were fitted to longitudinally analyze the nonlinear temporal interactions between various independent variables and bike-sharing usage change.

Our analysis builds on previous work on human mobility changes during the pandemic by (1) focusing on the spatiotemporal usage patterns of bike-sharing and comparing it with other modes of transport; (2) estimating the effects of various intrinsic (i.e. station characteristics) and extrinsic (i.e. land use, socio-economics, transportation facilities, infections, weather) factors to seek the roots of disparities in bike-sharing usage; (3) unraveling the differences in effects of aforementioned factors on bike-sharing usage between unperturbed periods and pandemic periods and (4) investigating the time-varying interaction effects over the course of the pandemic. Findings can help bike-sharing operators and local governments understand the demand change during the pandemic and inform the best practice that can adequately account for equity concerns when shared bikes and financial supports are allocated.

2. Literature review

2.1. Bike-sharing usage studies (during regular periods)

Sufficient studies on bike-sharing usage have already been well-documented (Fishman, 2016). Among these studies, dependent variables, i.e., the bike-sharing pickups or returns, are aggregated in different spatial units (stations, TAZs, census block groups, cycling routes, or cities) and separated by temporal features (weekdays versus weekends, peak hours versus non-peak hours) or user groups (younger versus elder, low-income versus medium/high-income, member versus casual) (Caspi and Noland, 2019; Chen et al., 2018; Faghih-Imani et al., 2014; Noland et al., 2016; Sun et al., 2018). Independent variables can be summarized as land use, socio-demographics, transit proximity, bicycle infrastructure, and weather conditions (Faghih-Imani et al., 2014; Noland et al., 2016; Sun et al., 2018; Wang et al., 2016).

Most prior findings are consistent. Areas with higher population density, more youngers, higher income, more cycling facilities, greater transit proximity, and better weather conditions are more likely to generate more cycling trips (Chen et al., 2017; Faghih-Imani et al., 2014; Noland et al., 2016; Shen et al., 2018). However, some controversial opinions are also proposed. For example, although most studies stated a complementary relationship between bike-sharing and transit (Noland et al., 2016), Campbell and Brakewood found a reduction in bus ridership after introducing bike-sharing and thus they claimed the relationship is substitutive rather than complementary (Campbell and Brakewood, 2017).

Besides the analysis of shared bike usage, some studies focus on examining bike-sharing users, including users' demographics, motivation, preference, and purpose. Several conclusions are consistent. For example, bike-sharing users are often younger, white males with higher education degrees and upper-to-middle income (Caspi and Noland, 2019; Shaheen and Cohen, 2019). Casual users are more likely to ride for leisure, while members are found to ride more for commuting (Kaviti et al., 2019; McKenzie, 2019; Wang and Lindsey, 2019). Opposite opinions also exist. For example, a recent study concluded that after partialling out other exogenous factors, members residing in lower-income neighborhoods generate more bike-sharing trips (Wang and Lindsey, 2019).

Various statistical methods are designed to model bike-sharing usage. Ordinary least squares (OLS) regression is not appropriate given the over-dispersion and non-normal nature of bike-sharing usage (Noland et al., 2016). The generalized regression models like Poisson regression, negative binomial model, and zero-inflated binomial model are widely used to address these problems (Faghih-Imani et al., 2014; Noland et al., 2016; Wang et al., 2016). Another common issue is the spatiotemporal autocorrelation when dealing with cross-sectional spatial data or longitudinal data. To control for this, several multi-level models combined with the autoregressive moving average (ARMA) or spatial additive terms are proposed (Caspi and Noland, 2019; Faghih-Imani et al., 2014; Hu et al., 2018; Noland et al., 2016; Sun et al., 2018; Wang et al., 2020). Recently, the endogeneity bias regarding the station capacity and bike-sharing usage has also drawn some attention. The error component in modeling bike-sharing usage is considered correlated with the station capacity since service operators prefer to allocate more resources in denser urban areas (Faghih-Imani and Eluru, 2016; Wang and Chen, 2020). To address this, structural equation modeling (for example, Two-Stage least squares (2SLS)) is introduced (Faghih-Imani and Eluru, 2016; Wang and Chen, 2020).

2.2. Bike-sharing usage and human mobility analysis (during the pandemic)

Mobility has proved to be a critical predicting factor of the spread of the COVID-19 pandemic. Mobility patterns are strongly correlated with decreased case growth rates (Badr et al., 2020; Xiong et al., 2020a). The

practice of social distancing can effectively reduce the infection rate of the disease. Therefore, most governments in affected areas have adopted lockdown and stay at home orders to mitigate the disease's spread.

Mobility flows have drastically reduced since the beginning of the COVID-19 pandemic (Badr et al., 2020; Hu et al., 2021; Xiong et al., 2020b). The magnitudes of drop, however, are not uniformly distributed for all modes of transport. Bike-sharing is proved to be a more resilient mode. In New York City, while the subway system had a rider drop of

90%, the bike-sharing system had a less 71% decrease and showed a faster rebound rate (Teixeira and Lopes, 2020). In Budapest, Hungary, COVID-19 decreased mobility by half, public transport experienced the most striking reduction of 80%, while cycling and bike-sharing saw the lowest decrease of 23% and 2%, respectively (Bucsky, 2020). The study done in Thessaloniki, Greece, suggests that COVID-19 will not markedly influence the number of bike-sharing users (Nikiforiadis et al., 2020). The main reason is that people consider bike-sharing as a safer mode to
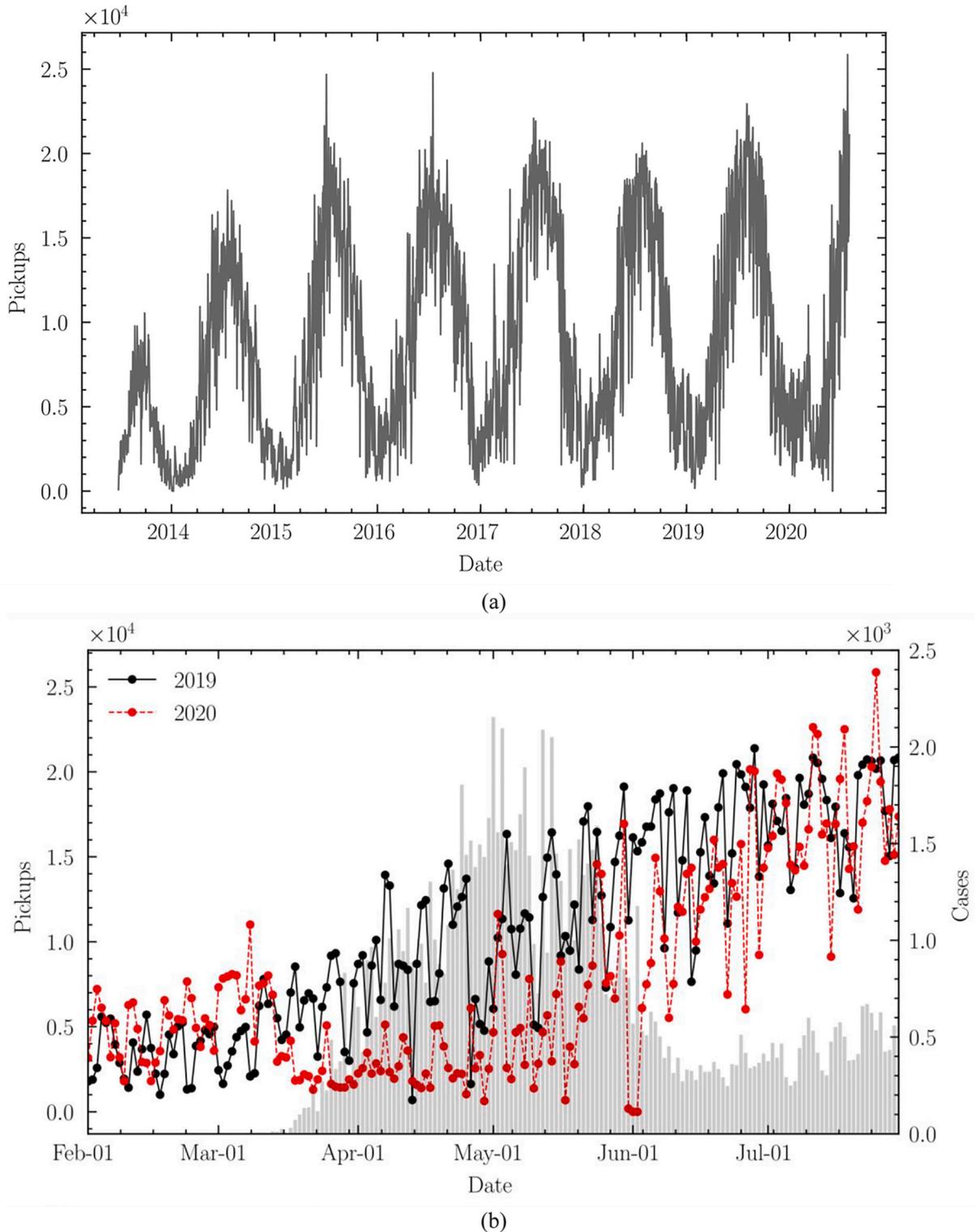

Fig. 1. Time series of bike-sharing pickups in Chicago. (a) From June 27th, 2013 to July 31st, 2020; (b) From February 1st, 2020 to July 31st, 2020.

limit contact during the pandemic. In the city of Chicago, by using a stated preference-revealed preference (SPRP) survey, Shamshiripour (Shamshiripour et al., 2020) found that transit, taxi, and ride-hailing services are the highest risky modes of transportation in resident's view. As a result, they might shift from ridesharing and public transit to modes that limit contact—such as walking, biking, and driving alone.

Also, concerns are rising about the economic consequences of lockdown policies and the potential disproportionate effect on populations with lower socioeconomic status (Hu et al., 2021). Bonaccorsi et al. (Bonaccorsi et al., 2020) have found that lockdown measures have a more substantial impact in areas with higher fiscal capacity, and mobility contraction in mobility is more salient in areas with more inequalities and lower incomes. Using New York City Citi Bike data, Pase et al. (Pase et al., 2020) found that wealthier neighborhood in Manhattan was more able to socially distance than more impoverished areas with a high number of essential low-wage workers. They also advocated for policies that help create a safer environment for cyclists because bike-sharing, in general, can provide a flexible and environmentally substantial alternative for shorter transportations as users are concerned about the risk of infection from the return to mass transit. In Beijing, China, share bike usage data showed a 60% decrease in mobility compared to the same period in 2019, with city centers being the most impacted area during and shortly after the pandemic (Chai et al., 2020).

3. Research design

3.1. Study area and background

The Divvy bike-sharing in the City of Chicago is chosen for empirical analysis. It is among the largest bike-sharing systems in the U.S. regarding the number of stations, bicycles, users, and transactions. As of July 2019, Divvy operated over 5800 bicycles at 608 stations, generating over 1,773,622 trips in 2019 (Wisniewski, 2019). The time series of daily pickups are visualized in Fig. 1. A rising trend is visible across recent years (Fig. 1 (a)). During the COVID-19, a precipitous fall in bike-sharing usage occurred in mid-March and reached its lowest in April; after that, the usage rebounded and gradually recovered to the near-regular status (Fig. 1 (b)). The monthly total numbers of pickups in 2019 and 2020 are also documented in Table 1.

Another reason to study the Divvy is due to the unprecedented outbreak of the COVID-19 pandemic in Chicago. Chicago was among the first U.S. cities significantly affected by the pandemic. On January 24th, 2020, the City of Chicago announced the first and the second confirmed cases in the U.S. The number of positive cases spiked exponentially since March 2020 (Fig. 1 (b), the bar plot). By May 1st, 2020, the number of positive cases in Cook County, Illinois, reached 1633 per day for a cumulative total of 36,513 (CSSE, 2020). At that time, Cook County had the second-highest number of confirmed cases across the nation only after New York County. On March 13th, 2020, the state government issued an emergency order to constrain inessential travel by closing all schools, bars, restaurants and restricting large gatherings to contain the virus's spread. As the virus spread further, the state enacted a more stringent stay-at-home order, enforcing fines and possible jail time. At firstly declared between March 21st and April 7th, the order was later

extended until April 30th, then May 29th.

3.2. Data and variables of interest

3.2.1. Dependent variables

Three dependent variables were considered in this study, including station-level average daily pickups from March 11st, 2019 to July 31st, 2019, station-level daily average pickups from March 11st, 2020 to July 31st, 2020, and station-level cumulative relative change from February 1st, 2020 to July 31st, 2020. We chose March 11st, 2020 as the beginning day of the COVID-19 pandemic as it is when WHO officially claims the COVID-19 as a pandemic. When studying the relative change, we started on February 1st, 2020. We want to include some pre-pandemic periods to better understand the change from pre-pandemic periods to post-pandemic periods. It is also worth noting we employed cumulative change rather than pointwise change is to eliminate the high randomness in daily fluctuation and smooth the time-series across the pandemic:

$$\overline{\phi}_{n:m}^{(j)} = \frac{1}{m-n} \sum_{t=n}^{m} \frac{y_t^{(j)} - \widetilde{y}_t^{(j)}}{\widetilde{y}_t^{(j)}} \tag{1}$$

where $\overline{\phi}_{n:m}^{(j)}$ is the cumulative relative change from day n to day m of station j; $y_t^{(j)}$ is the daily average pickups at station j in day t during 2020; $\widetilde{y}_t^{(j)}$ is the daily average pickups at station j in day t during 2019. In this study, we calculate the cumulative relative change ($\overline{\phi}_{n:m}^{(j)}$) from January 1st, 2020 but only included the data after February 1st, 2020 in the final analysis as the initial time-series is not stationary. This is because when $m - n$ is small, the cumulative relative change is approximate to the pointwise relative change.

Based on these variables, four models were built, including three cross-sectional models and a longitudinal model (see Table 2 for a summary). To better clarify the calculation of cumulative relative change as well as to clearly describe the overall temporal trends, the monthly total pickups and the corresponding cumulative relative changes are reported in Table 1. All dependent variables can be directly calculated using trip records downloaded from Divvy official website. For each trip, available information includes start and end timestamp, start and end station, and user types (casual or member). Several rules were then applied to filter out the outliers from the raw trip dataset. First, only trips with durations from 1 min to 6 h were kept, as trips with too short and too long duration may be due to data transmission error or abnormal travel. Then, stations with no trip generated during 2020 were dropped as those stations maybe be closed in 2020. Finally, stations with significantly lower trip generation but higher relative change (Threshold: the pointwise relative change is greater than 1000% while daily trips are lower than or equal to 2) were excluded. After applying these rules, 6.19% of trips were excluded from the final models.

The time-series of station-level cumulative relative change since February 1st, 2020 are shown in Fig. 2. Each transparent gray curve tracks one station's change, and the red and blue curves mark the mean and median of changes across all stations. Based on the time-varying patterns, we can divide the timeline into several parts as follows:

1) Period I (Regular period): the average bike-sharing pickup is greater in 2020 than in 2019. This could be due to the higher average temperature in January 2020 (0 °C) than in 2019 (−5 °C), and the growing popularity of bike-sharing in Chicago over recent years.

2) Period II (Pre-pandemic period): a slight increase is captured around March 11st, 2020. Again, this increase may be due to the higher average temperature in March 2020 (5 °C) than in 2019 (2 °C), and the pre-pandemic panic such that people were seeking alternative low-risk travel modes for the forthcoming lockdown.

3) Period III (During the pandemic): A sharp decrease occurs between March 11st, 2020 and June 5th, 2020 (the day when the local

Table 1
Monthly total pickups and corresponding cumulative relative change.

Month	Pickups in 2020	Pickups in 2019	Cumulative change	Cumulative relative change
1	140,653	102,461	38,192	0.373
2	132,017	95,357	74,852	0.378
3	136,729	164,328	47,253	0.130
4	81,754	263,107	−134,100	−0.214
5	192,751	364,477	−305,826	−0.309
6	330,603	472,144	−447,367	−0.306
7	530,772	553,723	−470,318	−0.233

Table 2

Summary of variables.

		Description	Model	Mean	St.d.	Min.	Max.
Dependent Variable							
Average Daily Pickups (2019)		The station-level daily average number of pickups from March 11st, 2019 to July 31st, 2019	I	25.522	28.072	0.519	229.333
Average Daily Pickups (2020)		The station-level daily average number of pickups from March 11st, 2020 to July 31st, 2020	II	16.376	14.584	0.453	80.310
Cumulative relative change (By July 31st, 2020)		Station-level cumulative relative change by July 31st, 2020	III	−0.054	0.382	−0.742	1.990
Cumulative relative change (Across the pandemic)		Station-level cumulative relative change from February 1st, 2020 to July 31st, 2020	IV	0.095	0.463	−0.799	2.977
Independent Variable							
Socio-demographic (Census block group level)	Prop. of Male	The proportion of males	I - IV	0.497	0.069	0.306	0.712
	Prop. of Age_25_40	The proportion of people aged between 25 and 40	I - IV	0.375	0.154	0.000	0.706
	Prop. of Age_40_65	*The proportion of people aged between 40 and 65*	*–*	*0.258*	*0.090*	*0.016*	*0.842*
	Prop. of White	The proportion of White	I - IV	0.642	0.242	0.000	1.000
	Prop. of Black	*The proportion of Black*	*IV*	*0.156*	*0.233*	*0.000*	*1.000*
	Prop. of Asian	The proportion of Asian	I - IV	0.120	0.132	0.000	0.949
	Median Income	The median household income, in 10^3/household.	I - IV	86.660	40.988	12.661	214.659
	Prop. of College Degree	The proportion of people with education attainment equal to/higher than college	I - IV	0.640	0.243	0.000	1.000
	Prop. of Car	The proportion of people commuting with private cars	I - IV	0.408	0.166	0.000	0.828
	Prop. of Transit	*The proportion of people commuting by transit*	*IV*	*0.321*	*0.147*	*0.000*	*0.902*
	Prop. of Walk Bike	*The proportion of people commuting by walk or bike*	*–*	*0.177*	*0.161*	*0.000*	*0.643*
	Prop. of Goods & Product Jobs	The proportion of jobs in goods and producing sectors	I - IV	0.077	0.163	0.000	1.000
	Prop. of Utilities Jobs	The proportion of jobs in trade, transportation, and utility sectors	I - IV	0.146	0.216	0.000	1.000
	Population Density	Population density, in 10^3 persons/sq. mile	I - IV	21.334	19.280	0.000	175.319
	Job Density	Job density, in 10^3 jobs/sq. mile	I - IV	2.141	5.405	0.005	38.510
COVID-19 features (ZIP code level)	No. of Cases	The number of cumulative COVID-19 cases, in 10^3	I - IV	0.382	0.268	0.000	1.704
	Infection Rate	*The infection rate of COVID-19 (cumulative COVID-19 cases/ population)*	*–*	*0.007*	*0.004*	*0.000*	*0.020*
Land use (500 m buffer level)	Prop. of Commercial	The proportion of commercial land	I - IV	0.132	0.105	0.000	0.564
	Prop. of Industrial	The proportion of industrial land	I - IV	0.032	0.064	0.000	0.449
	Prop. of Institutional	The proportion of institutional land	I - IV	0.086	0.112	0.000	0.860
	Prop. of Open space	The proportion of open space land	I - IV	0.068	0.137	0.000	0.891
	Prop. of Residential	The proportion of residential land	I - IV	0.296	0.158	0.000	0.613
Transportation features (500 m buffer level)	Road Density	Road density, in mile/sq. mile, including arterial roads, secondary roads, and minor roads	I - IV	54.082	16.660	18.778	113.748
	Bike Route Density	Bike route density, in mile/sq. mile	I - IV	3.876	2.356	0.000	11.789
	Transit Ridership	Daily average transit ridership, in 10^3, including bus alighting, boarding, and rail system ("L" system) rides	I - IV	12.798	21.238	0.000	138.883
	No. of Nearby Rail Stations	*The number of nearby rail stations*	*–*	*0.868*	*1.597*	*0.000*	*11.000*
	No. of Nearby Bus stops	*The number of nearby bus stops*	*IV*	*22.622*	*10.718*	*0.000*	*61.000*
Station characteristics (Station Level)	Capacity	The number of docks in the bike-sharing station	I - IV	18.857	7.797	0.000	55.000
	The capacity of Nearby Bike Stations	*The total number of docks in nearby bike-sharing stations*	*–*	*60.499*	*77.988*	*0.000*	*379.000*
	Distance to Nearest Bike Station	The distance to the nearest bike-sharing station, in miles	I - IV	0.249	0.114	0.032	0.856
	Distance to City Center	*The distance to the city center, in mile*	*IV*	*4.153*	*2.509*	*0.000*	*13.039*
Control Variable							
Temporal seasonality	Month	Month, from 1 (January) to 12 (December)	IV	–	–	2.000	7.000
	Week	Day of the week, from 0 (Monday) to 6 (Sunday)	IV	–	–	0.000	6.000
	Is Holiday	If the day is a holiday, 1; else 0.	IV	–	–	0.000	1.000
	Time Index	The difference in the day from the current date to March 11st, 2020	IV	–	–	0.000	141.000
Weather condition	Precipitation	Daily precipitation, in mm	IV	3.540	9.191	0.000	74.088
	Max. Temperature	Daily maximum temperature, in Celsius	IV	17.761	10.773	−9.525	35.367
	Δ Precipitation	Difference between daily precipitation in 2019 and on the same day of 2020, in mm	IV	−0.525	11.508	−51.352	71.024
	Δ Max. Temperature	Difference between daily maximum temperature in 2019 and on the same day of 2020, in Celsius	IV	1.270	6.300	−18.640	18.500

Note: Models I, II, III refer to the cross-sectional models using the regular (2019) average bike-sharing usage, the pandemic (2020) average bike-sharing usage, and the cumulative relative bike-sharing usage change (i.e., 2020 versus 2019) as the dependent variables respectively. Model IV refers to the longitudinal model.

government lifts stay-at-home order in Chicago), which can be explained by the stay-at-home restriction and the virus's threat.
4) Period IV (Mobility rebound): After June 5th, 2020, a slow rebound is observed. As of July 31st, 2020, the cumulative trips have almost recovered to regular status.

3.2.2. Independent variables and control variables
Independent variables include land use, socio-demographics,

COVID-19 related features, transportation features, and station characteristics. When conducting longitudinal analysis, we further controlled for temporal variables, including weather conditions and temporal seasonality, by incorporating the effects of precipitation, temperature, weekly and monthly patterns, and holidays into the models (see Table 2 for a summary). Data sources of the independent variables are listed as follows: land use from the Chicago Metropolitan Agency for Planning (CMAP); census block group level socio-demographic features from the
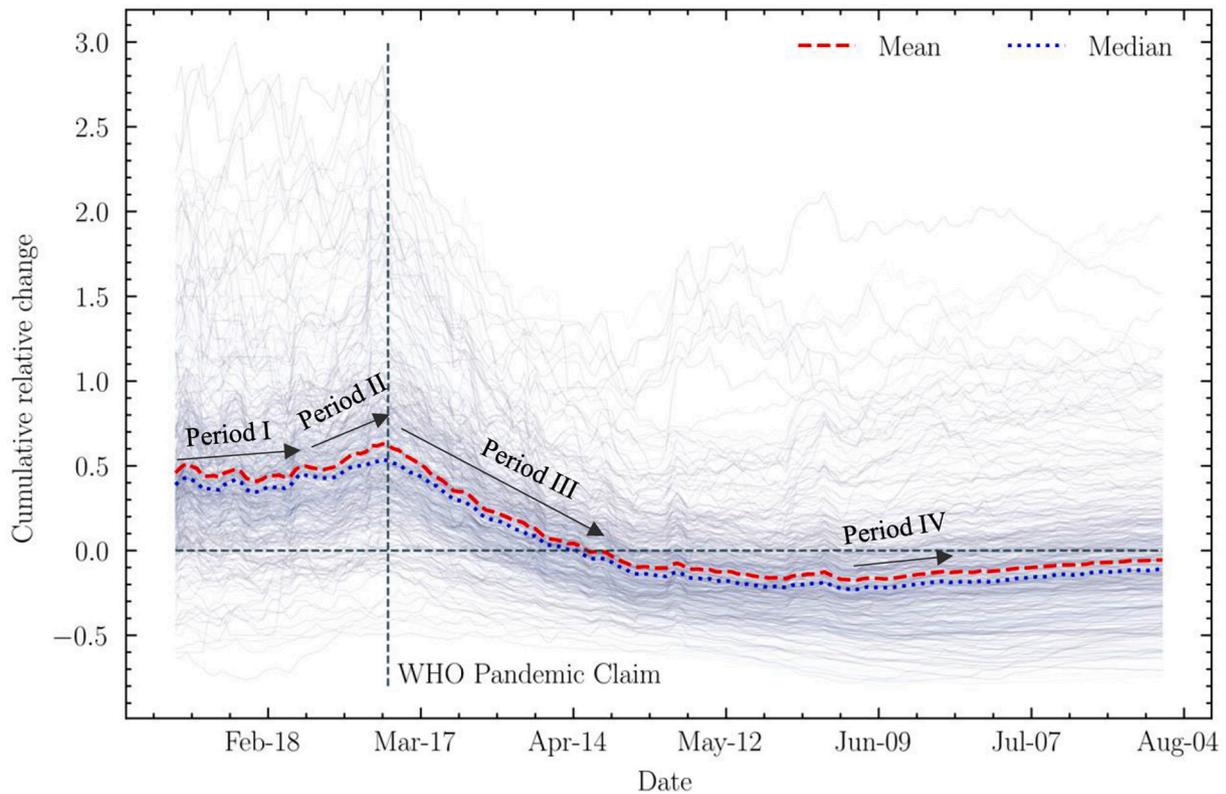
Fig. 2. Station-level cumulative relative change during COVID-19.

2018 American Community Survey (ACS) 5-year estimates; zip-code level counted COVID-19 positive cases and station level transportation features from Chicago Data Portal; employment information from the LEHD Origin-Destination Employment Statistics (LODES) datasets; and weather conditions from the National Climatic Data Center (NCDC).

All spatial variables were calculated based on the station service area but were collected in different spatial units like zip codes and census block groups. These variables were distributed to station service areas weighted by the share of each zipcode or block-group area with the station service area (Noland et al., 2016). The service area of each bike-sharing station is defined by a cycle with a 500-m radius. The underlying assumption is that people only walk for a 500-m distance to access a shared bike. Otherwise, people may choose alternative modes. Similar distances have been used in previous studies (Wang and Chen, 2020). To the concern of Modifiable Area Unit Problem (MAUP), we also tested different radiuses varying from 0.3 km to 1 km with a step of 100 m and found models present consistent performances.

Variable selection was performed to determine the optimal variable set. The variance inflation factor (VIF) was first calculated to test the multicollinearity, and VIFs greater than five were excluded. Then, stepwise regression was employed to help select the independent variables based on the smallest AIC. Variables in the *Italic* text in Table 2 were excluded from the models, either because of the high multicollinearity with other variables or the low capability in explaining the dependent variables. It is worth mentioning the VIF test and stepwise selection does not yield the same optimal variable set for all four models. Thus, it is possible that some variables are excluded from some models but still retain in other models.

An important caveat here is that most of our independent variables were deduced on an aggregate (census block group or zip code) level in the absence of available information on the individual (Divvy user) level. As such, conclusions drawn from this study should not be extrapolated to individuals considering the possibility of an ecological fallacy. Although there is currently no way to overcome such problems

that are inherent to all statistical inferences using aggregated data, our findings could help policy evaluation and intervention which are often targeted at an aggregate (i.e. community, county, or state) level.

3.3. Methodology

3.3.1. Cross-sectional analysis using the generalized additive model (GAM)

The generalized additive model (GAM) (Wood, 2003) was employed to construct statistical inference. GAM (Wood, 2003) is a semi-parametric model with a linear predictor involving a series of additive non-parametric smooth splines of covariates. Compared to the ordinary least squares (OLS) linear regression, GAM is more flexible with fewer assumptions, which is useful when data fail to meet OLS assumptions, such as normality and homogeneity. Additionally, a noticeable advantage of GAM lies in its capability and flexibility to handle different nonlinear effects (Wood, 2003). By changing spline functions, various nonlinear effects can be fitted under one framework, such as random effects, nonlinear interactions, and spatiotemporal autocorrelations (Hu et al., 2018; Wang et al., 2020).

When conducting cross-sectional analysis on bike-sharing usage, the over-dispersion and the spatial autocorrelation are two main issues that need the GAM to address (Noland et al., 2016). Similar to prior studies (Noland et al., 2016; Wang et al., 2016), we assume bike-sharing pickups follow a count-based negative binomial (NB) distribution. NB distribution introduces an additional free parameter to relax the assumption that expectation and variance are equal. Besides NB distribution, we also tested other distributions such as normal distribution and Poisson distribution. GAMs under the NB distributions present the lowest AIC, indicating the NB distribution fits data best. An additive term to capture the spatial coordinate interaction is also attached (Wood, 2017). The final formulation of three GAMs are as follows:

$$Y^{(1)} \sim NB\left(\mu_1 \mu_1 + \frac{\mu_1{}^2}{k_1}\right), Y^{(2)} \sim NB\left(\mu_2 \mu_2 + \frac{\mu_2{}^2}{k_2}\right), Y^{(3)} \sim N\left(\mu_3 \sigma_3{}^2\right) \qquad (2)$$

$$g^{(r)}\left(Y_i^{(r)}\right) = \beta_0^{(r)} + \sum_{m=1}^{M} \beta_m^{(r)} X_{m,i} + \widetilde{S}_i + \vartheta_i^{(r)} \tag{3}$$

where $Y^{(1)}$, $Y^{(2)}$, $Y^{(3)}$ are station-level average daily pickups from March 11st, 2019 to July 31st, 2019, station-level daily average pickups from March 11th, 2020 to July 31st, 2020, and station-level cumulative relative change by July 31st, 2020, respectively; μ_1, μ_2, μ_3 are the mean of $Y^{(1)}$, $Y^{(2)}$, $Y^{(3)}$; k_1, k_2 are the corresponding dispersion parameters, and σ_3 is the standard deviation; $g^{(r)}(.)$ is the link function of the rth dependent variable $Y^{(r)}$, where $r = 1, 2, 3$; when $Y^{(r)}$ follows the NB distribution, $g^{(r)}(.)$ is a logarithmic link and when $Y^{(r)}$ follows the normal distribution, $g^{(r)}(.)$ is an identity link; $\beta_0^{(r)}$ is the overall intercept for the rth dependent variable; $\beta_m^{(r)}$ is the mth coefficient of the mth independent variables X_m, and M is the number of independent variables; $\widetilde{S}_i$ is the spatial coordinate interaction of station i; $\vartheta_i^{(r)}$ is the error term.

3.3.2. Longitudinal analysis using the generalized additive mixed model (GAMM)

We further developed a set of longitudinal models to analyze the nonlinear temporal interactions among different independent variables and cumulative relative change in bike-sharing usage. As a longitudinal analysis with repeated observations overtime at each station, the non-independence among repeated observations and the heterogeneous temporal variability should be addressed. Multi-level (also named mixed) models are widely used to handle the panel data (Wolfinger and O'connell, 1993). However, traditional mixed models are linear based and cannot obtain high performance under data with significant nonlinear nature. Hence, a generalized additive mixed model (GAMM) structure was involved, with several additive smooth terms besides the linear fixed effect to address the heterogeneous covariance structures. To specific, the additive terms in this study include (Wood, 2017):

1) Nonlinear random effects across all stations to capture the unobserved heterogeneity.
2) Temporal seasonality, including weekly and monthly patterns.
3) Autoregressive term to address temporal autocorrelations in residual.
4) Spatial interactions to address spatial autocorrelations in residual.

Besides the above additive terms, an interaction term between the independent variable of interest and time index was included to explore the nonlinear interaction, controlling for other factors like weather, seasonality, holidays, and other variables with linear fixed effects:

$$g(Y_{i,t}) = \beta_0 + \sum_{k=1}^{K} \beta_k F_{k,i,t} + \sum_{l=1}^{L} f_l\left(N_{l,i,t}\right) + \widetilde{f}_T\left(X_{i,t} \times T_{i,t}\right) + \widetilde{S}_i + \widetilde{R}_i + AR_{i,t,P}$$
$$+ \vartheta_{i,t} \tag{4}$$

$$AR_{i,t,P} : Y_{i,t} = c_i + \sum_{p=1}^{P} \varphi_{i,p} Y_{i,t-p} + \varepsilon_{i,t} \tag{5}$$

where $Y_{i,t}$ is the cumulative relative change in station i on day t; $g(.)$ is the link function, here we use the identity links assuming the cumulative relative change follow a normal distribution; β_0 is the overall intercept; β_k is the kth coefficient of fixed effects; K is the total number of fixed effects; $F_{k,i,t}$ refers to the kth fixed control variable in station i on day t, including weather conditions, holidays, and other variables except for X_i; L is the total number of control variables that present nonlinear relationships; $f_l(.)$ is a low rank isotropic smooth function and $N_{l,i,t}$ denotes the lth control variable with nonlinear effects, here $N_{l,i,t}$ includes all the temporal seasonality; $X_{i,t}$ is the independent variable nonlinearly interplaying with the time index $T_{i,t}$ in station i on day t; $\widetilde{f}_T($) is the smooth interaction functions; $\widetilde{S}_i$ is the spatial coordinate

interaction term of station i to capture the spatial autocorrelation; $\widetilde{R}_i$ is the random effect of station i fitted by the spline function penalized by ridge penalty; $\vartheta_{i,t}$ is the error term; $AR_{i,t,P}$ is an autoregressive term for station i with order P (here $P = 1$), with expression shown in Eq. (5): where c_i is the intercept; $\varphi_{i,t}$ is the coefficient of the pth lagged $Y_{i,t}$; $\varepsilon_{i,t}$ is the white-noise.

The estimation of GAMM is implemented in "*mgcv*" package using *R* (Wood, 2017). The variance components are estimated by the fast-Restricted Maximum Likelihood Estimation computation (fREML). To speed up the estimation process, this study employed an approach based on the discretization of covariate values and C code level parallelization (Li and Wood, 2020). When fitting model covariates, it takes only a discrete set of values substantially smaller than the sample size, which can reduce the computing time by two to three orders with very few approximation errors.

4. Results

4.1. Descriptive analysis

This section reports the descriptive analysis of the bike-sharing trips. For each year, trips generated between March 3rd and July 31st were compared and reported in Table 3. Compared with 2019, a 32.35% drop in the total number of trips is observed during the pandemic. The components of trips in terms of user types have also considerably altered. The proportion of trips generated by members decreased from 75.04% in 2019 to 56.24% in 2020. Considering members ride more for commuting while casuals ride more for leisure (Kaviti et al., 2019; McKenzie, 2019; Wang and Lindsey, 2019), it is reasonable that members suffer the most striking drop due to the work-from-home policies. Another interesting finding is that the average trip duration and trip distance both increased during the pandemic. A similar phenomenon is found in China, where commuters have also been using shared bikes for longer rides as the data demonstrates that trips longer than 3 km have doubled since the pandemic (Wenyan, 2020). We argue such changes

Table 3
Description of bike-sharing trips.

Trip features				
	Period	Total	Casual ratio	Member ratio
Number of trips	2019	1,773,622	24.96%	75.04%
	2020	1,199,923	43.76%	56.24%
	Year	Mean	St.d.	Median
Trip duration (minute)	2019	19.493	23.063	12.650
	2020	27.125	31.286	17.933
Trip Haversine distance (mile) [a]	2019	1.382	1.192	1.019
	2020	1.398	1.255	1.096
Network features [b]				
	Year	Value		
Self-loops ratio	2019	4.58%		
	2020	12.69%		
Diameter (Weighted by Haversine distance)	2019	23.704		
	2020	24.769		
Clustering coefficient	2019	0.696		
	2020	0.677		
Number of communities (Infomap, weighted by the number of trips)	2019	17		
	2020	11		

Note: a) 2019 means March 3rd, 2019 to July 31st, 2019; 2020 means March 3rd, 2020 to July 31st, 2020. b) Since Divvy does not report the network trip distances, we calculated the Haversine distance between trip start and end station. c) Diameter of a graph means the length of the longest geodesic. The clustering coefficient (also called transitivity) is the probability that the adjacent vertices of a vertex (i.e., station) are connected (i.e., at least one trip is generated). The number of communities is calculated based on the Infomap algorithm (Rosvall et al., 2009). All network features are calculated using the package "*igraph*" (Csardi and Nepusz, 2006).

are due to the increase in the proportion of trips for exercise and leisure. These trips are more likely to have longer durations and longer distances compared with commuting trips.

Fig. 3 presents the temporal patterns of pickups. Daily profile in 2019 presents a two-peak "commuting" pattern, while it changes to a one-peak "leisure" pattern in 2020. Also, weekly profile shifts from "week-days more popular" in 2019 to "weekends more popular" in 2020. These changes further support the argument that the proportion of commuting trips has declined during the pandemic while the proportion of exercise/leisure trips has increased.

We further compared network features by constructing the bike-sharing trip flow network as a directed graph weighted by trip volume between each station pair (summarized in Table 3). The self-loops ratio (i.e., the round-trip ratio) increases from 4.58% in 2019 to 12.69% in 2020. It is plausible since round trips are always considered as leisure trips (Noland et al., 2016). Also, a slight increase in the graph's diameter and a decrease in the clustering coefficient in 2020 were observed, indicating the spatial network structure of bike-sharing trip flow becomes sparser and less compact during the pandemic.

We sequentially conducted the community detection based on the Infomap algorithm, a popular community finding method designed particularly for the directed weighted graph to minimize the expected description length of a random walker trajectory in the graph (Rosvall et al., 2009). The purpose of community detection is to divide the network into clusters (i.e., communities) of nodes (i.e., bike-sharing stations) with dense connections internally and sparser connections between clusters. Results are geographically mapped in Fig. 4, with each color presenting one community. We found the number of communities decreases from 17 in 2019 to 11 in 2020, indicating the pandemic dramatically curtailed the strength of connection and contracted the complexity of the bike-sharing network structure. People may also ride longer to reach farther stations for exercise and cancel many short-distance stroll-around trips, which further weakens travel connections with nearby stations and flattens the network structure.

The spatial distributions of the first two dependent variables in Table 2 are shown in Fig. 4. The size of points varies by the value of average pickups, while the color varies by the type of communities derived from the Infomap algorithm. The number of trips suffers an apparent shrinkage in 2020, and the community structure also presents striking change. From a spatial perspective, stations located around the city center show the most drastic change. In 2019, more than six different communities are surrounding the city center; but it shrinks to only one community in 2020. This shrinkage indicates such area presents the most complicated trip connections during regular periods.

However, due to the pandemic, the connections are substantially weakened, rendering the converge and degradation of network structure.

The spatial distributions of cumulative relative change by July 31st, 2020 (i.e., the third dependent variable in Table 2) are shown in Fig. 5. We split the changes by the signs of their values and plot their absolute values separately. Therefore, in each subfigure, a larger spot represents a greater change. The small black circulars in each subfigure are those with opposite signs. We found that stations with positive cumulative changes are mostly distributed in the suburbs. At the same time, those suffering greater usage decreases are mainly located near the city center. Such finding further confirms the spatial heterogeneity in relative change of bike-sharing usage and necessitates the examination of factors related to such heterogeneity.

4.2. Comparison with other modes of transport

Although human movement curtailed substantially during the pandemic, the scales of decline across different modes of transport were not uniform. Of particular interest is to compare the bike-sharing with other modes like driving, walking, transit, and total human travel to see whether bike-sharing is more resilient or not. To achieve this, different data sources besides the Divvy were leveraged, including the *Apple Mobility* (Apple, 2020), which is currently the only public data source providing the COVID-19 mobility trend broken down by different modes of transport; and the *SafeGraph Social Distancing Metrics* (SafeGraph, 2020), which provides the overall human movement statistics derived from deidentified large-scale mobile phone data. More concretely, Apple Mobility approximates human mobility by the number of daily requests for directions from Apple Maps users. SafeGraph aggregates location-based service (LBS) data from over 45 million mobile devices and measures the frequency of visits of over 4.4 million Point-of-Interests (POIs) in the U.S. All data were collected from anonymized users who have opted-in with complete anonymity regarding their identity and personal details to provide access to their location data. In this study, only movements located in Cook County, Illinois, were retrieved. The temporal evolution was visualized in Fig. 6 and the monthly average relative volume was documented in Table 4. It should be noted that Apple Mobility only provides the relative volume compared to the baseline volume on January 13th, 2020. To comply with that, all other data including SafeGraph POI visits and Divvy trips were standardized by dividing daily volume by the corresponding volume on January 13th, 2020.

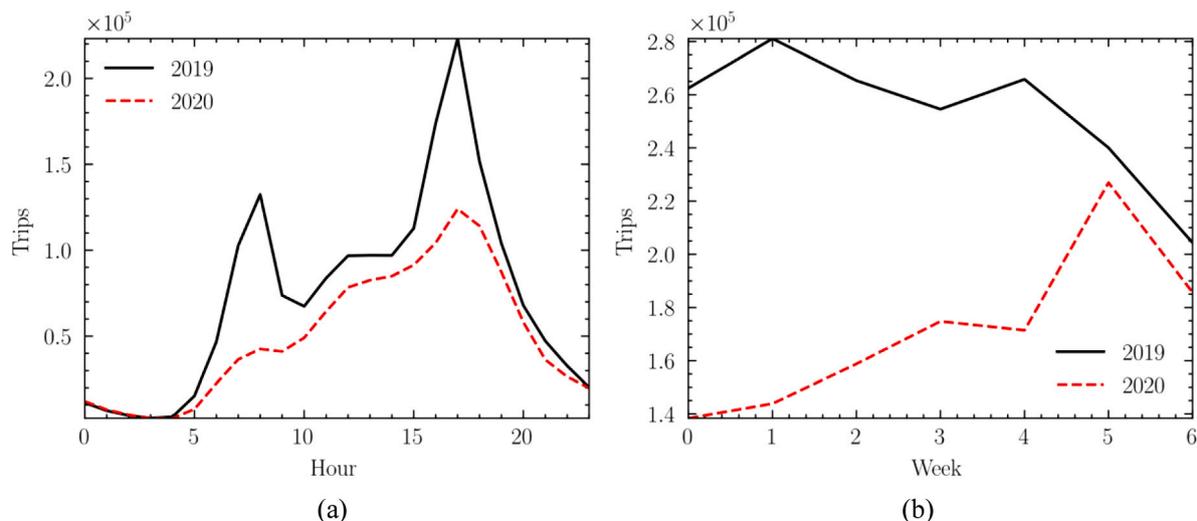The overall mobility evolution trends across different modes are

Fig. 3. Temporal patterns of Divvy bike-sharing pickups. (a) Hourly total trips; (b) Weekly total trips from 0 (Monday) to 6 (Sunday).
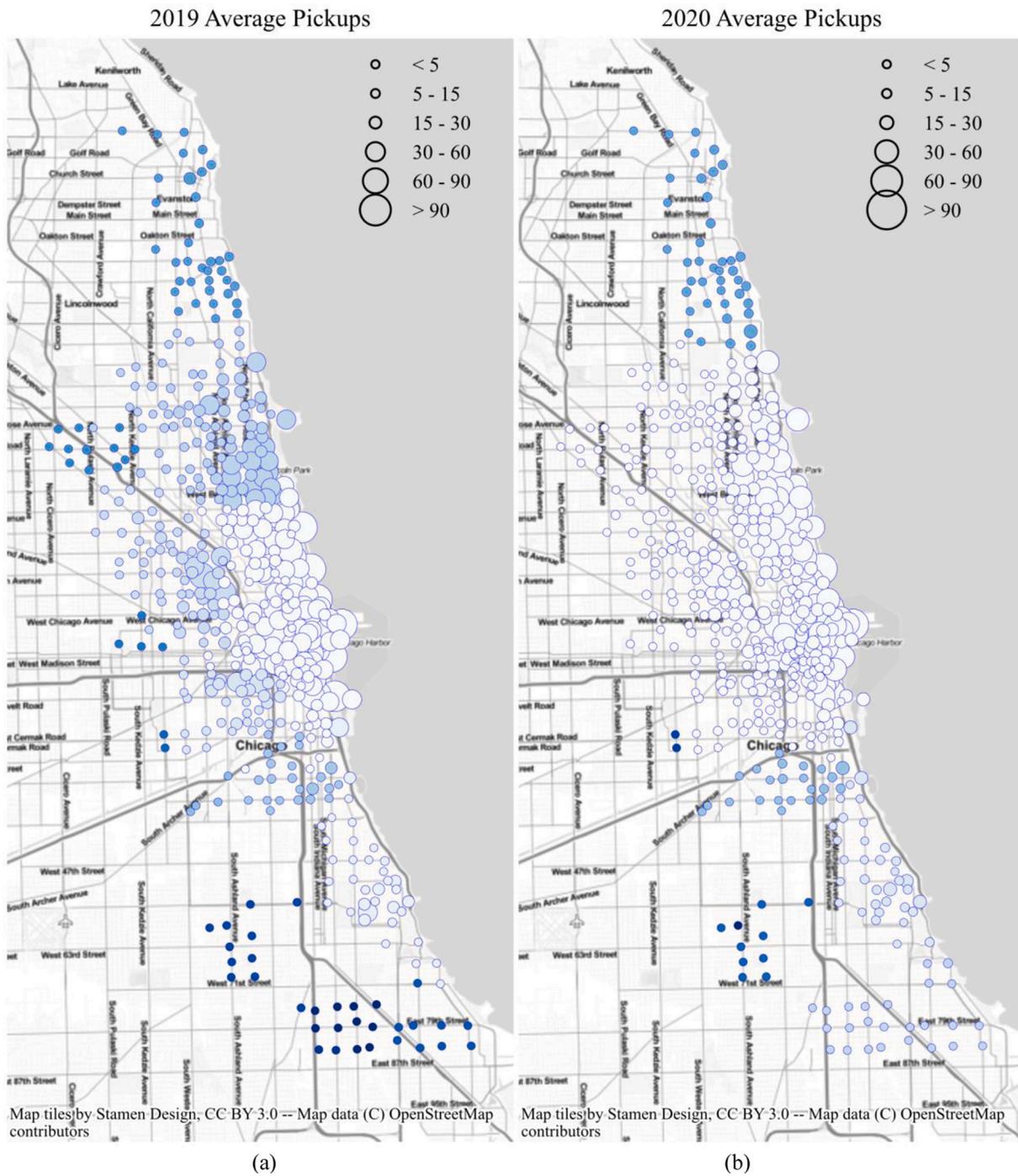
2019 Average Pickups

2020 Average Pickups

Fig. 4. Spatial patterns of Divvy bike-sharing pickups. (a) Average daily pickups from March 11st, 2019 to July 31st, 2019; (b) Average daily pickups from March 11st, 2020 to July 31st, 2020.

similar. All types of mobility plummeted steeply around mid-March, reached their nadirs in April, and afterwards steadily rebounded till the end of the observation period. Pronounced differences are visible regarding the degree of decline and speed of recovery. Transit suffers the most severe hit, losing the greatest percentage of trips (changing to 21.3% of baseline by April) and recovering at the slowest speed (reaching 45.8% of baseline by July). Bike-sharing, on the contrary, exhibits the fastest rebound speed and greatest rebound scale, with the total number of trips increasing to 284.0% of the baseline by the end of July. Driving and walking present similar patterns, recovering at a speed lower than bike-sharing and reaching 137.5% and 131.6% of the baseline respectively by July. The total number of travels exhibits the

average pattern of all modes, rebounding at a moderate speed and recovering to 82.5% of the baseline by the end of observation period.

Although bike-sharing displays the most resilient and robust trend, which also dovetails with previous studies (Bucsky, 2020; Teixeira and Lopes, 2020), it would be inappropriate at this stage to infer that bike-sharing has the ability to substitute other more vulnerable options like transit during the pandemic. Some other reasons may also account for this distinctive rebound trend of bike-sharing. First, cycling is more sensitive to temperature and its intrinsic growing trend is typically steeper when moving through winter to summer compared with other modes (the 2019 temporal trend in Fig. 1 (b) can stand as evidence). If the pickups on the same day of 2019 are used as baseline, the curve of
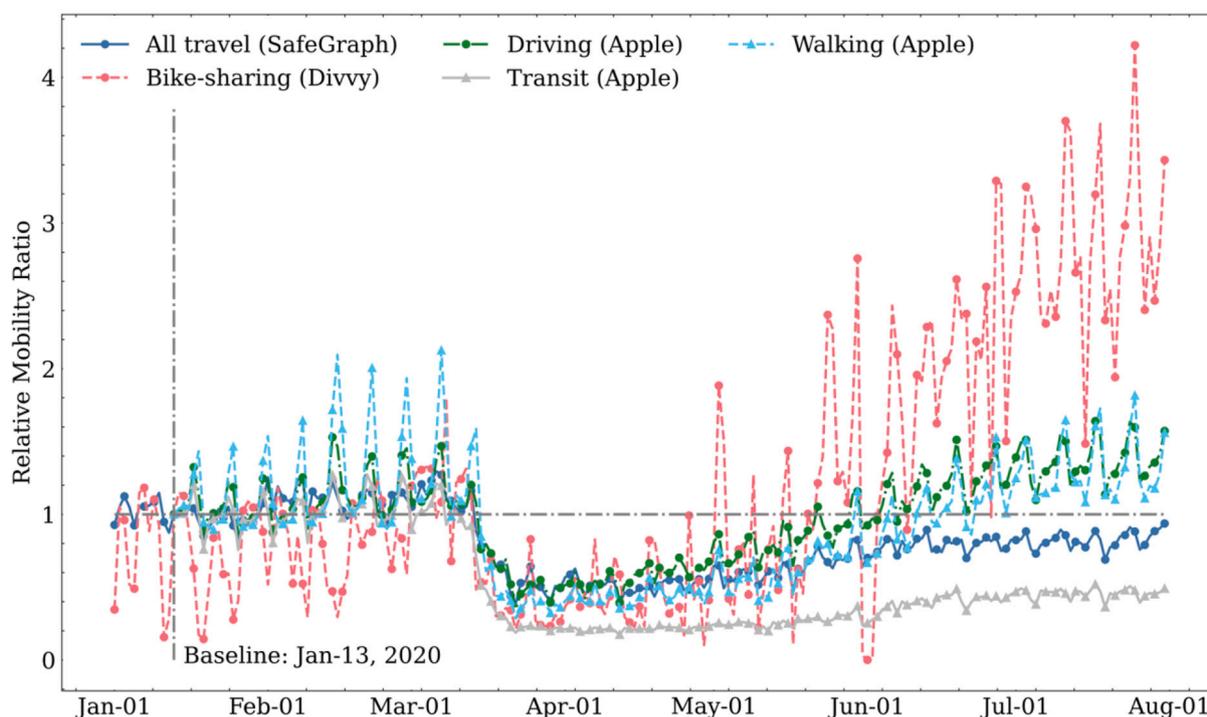
Cumulative Relative Change (+)

Cumulative Relative Change (|-|)

Fig. 5. Spatial patterns of Cumulative relative changes by July 31st, 2020. (a) Cumulative relative changes with positive values; (b) Absolute of cumulative relative changes with negative values.

relative bike-sharing mobility ratio would be flattened. Second, the total number of trips generated by Divvy users is largely constrained by the total number of available devices like shared bikes, docks, and stations. Hence, the continuous system expansion of Divvy itself also contributes to the high rebound rate. Nonetheless, motivated by the trend we can document that bike-sharing serves as a more important option during the pandemic potentially due to its high health benefit and low risk of contagion. Policymakers could think about how to provide safer services like bike-sharing to help maintain connectivity between communities that are seeing sustained flows during the crisis.

4.3. Inferential analysis of cross-sectional models

The results of three cross-sectional GAMs are reported in Table 5. The same independent variables are used in all three models, with the addition of the number of COVID-19 cases in model II and Model III. Goodness-of-fit indexes (adjusted R^2) are 0.527, 0.610, and 0.400 for the three models, respectively, indicating that the GAMs fitted the data well. The goodness-of-fit for Model III is worse than the other two models, which may because the cumulative relative changes are more fluctuated and harder to capture. Two parts are included in the results: the parametric coefficients, corresponding to the linear fixed effects, and the non-parametric smooth terms, corresponding to the nonlinear effects.

Fig. 6. Temporal evolution of relative volume of different modes of transport across the pandemic, from January 1st, 2020 to July 31st, 2020, compared to a baseline volume on January 13th, 2020.

Table 4
Monthly relative volume of different modes of transport from January 1st, 2020 to July 31st, 2020, compared to the baseline volume on January 13th, 2020.

Month	All travel	Bike-sharing	Driving	Transit	Walking
1	0.992	0.753	1.050	0.993	1.070
2	1.105	0.775	1.137	1.044	1.248
3	0.815	0.732	0.821	0.599	0.843
4	0.514	0.452	0.573	0.213	0.439
5	0.639	1.031	0.840	0.263	0.654
6	0.788	1.828	1.180	0.393	1.014
7	0.825	2.840	1.375	0.458	1.316

Note: The reason that the relative ratio of bike-sharing usage is lower than 1 in January is that the baseline date, January 13th, 2020, is Monday and bike-sharing is more popular on weekdays during regular periods (see Fig. 3 (b)).

Only spatial interaction is included in the nonlinear term, and two of them (i.e., Model I and II) are statistically significant. The insignificant sign of the spatial interaction in Model III indicates that the spatial distribution of relative changes is more randomized than average pickups.

The reason for fitting the three models is to comprehensively understand the differences and similarities regarding bike-sharing usage determinants during regular and pandemic periods. Specifically, Model I and II uncover what factors significantly correlate with the *absolute bike-sharing usage* during regular and pandemic periods, while Model III directly examines what factors contribute to the *relative change* in bike-sharing usage triggered by the pandemic. By comparing coefficients in the three models, three questions can be answered: 1) which region prefers to riding shared bikes during unperturbed periods; 2) which region continues generating shared bikes trips during the pandemic and 3) which region suffers the greatest relative change in riding shared bikes during the pandemic.

Regarding socio-demographics, the proportion of white and educated residents and the population density all present significant positive signs in Model I and Model II, while the proportion of commuting with private cars present significant negative signs. These indicate that regardless of the pandemic, bike-sharing is always more popular among regions with more white and educated residents, higher population density, and fewer commuters driving private cars. Such findings are highly consistent with various previous studies (Caspi and Noland, 2019; Fishman, 2016; Shaheen and Cohen, 2019). The median household income, on the contrary, presents a slightly significant positive sign in Model I, but changes to insignificant in Model II. This implies that regions with higher income generates more bike-sharing trips during regular periods, but not during the paramedic. Such arguments are further confirmed by Model III, which shows the proportion of white and Asian residents and the median household income present significant negative relationships. Alternatively, *regions with higher income and more white and Asian residents suffer a more significant relative decrease in bike-sharing trips during the pandemic*. This finding is in line with various prior studies regarding the human mobility changes during COVID-19, which claims that lower-income and colored workforce experienced the least change in travel behavior (Bliss et al., 2020; Brough et al., 2020; De Vos, 2020; Hu et al., 2021; Pase et al., 2020; Sy et al., 2020; Wilbur et al., 2020). We argue the main reason may because "essential" workers are mostly non-white, poorly-paid, and required to travel to their workplaces regardless of the stay-at-home orders (Bliss et al., 2020; Wilbur et al., 2020). Besides, lower car ownership, lower awareness of virus risks, and less flexibility to change to other modes may be other potential reasons (Brough et al., 2020).

As for land use, the proportion of industrial lands present significant negative relationships in both Model I and II, while the proportion of open space presents significant positive relationships. In other words, regions with more industrial lands and less open space generate fewer trips in both periods. Prior studies found similar results (Caspi and Noland, 2019; Shen et al., 2018; Sun et al., 2018). The residential lands, however, present opposite signs between the two periods. A negative relationship with bike-sharing usage is observed during regular periods, but the sign flips to positive during the pandemic. Findings in Model III further ascertain the above arguments. Results show that the proportion of open space and residential lands are significantly positively related to relative change, indicating *smaller relative decrease in bike-sharing usage*

Table 5
Results of cross-sectional analysis.

		I. Average Daily Pickups (2019)				II. Average Daily Pickups (2020)				III. Cumulative relative change (by 2020/07/31) [b]			
	Parametric coefficients												
		Coeff.	St.d. Err.	P-value		Coeff.	St.d. Err.	P-value		Coeff.	St.d. Err.	P-value	
	(Intercept)	1.425	0.332	0.000	***	1.412	0.347	0.000	***	−0.192	0.203	0.346	
Socio-demographic	Prop. of Male	−0.209	0.372	0.574		−0.183	0.377	0.627		0.234	0.225	0.300	
	Prop. of Age_25_40	0.091	0.218	0.677		0.134	0.224	0.551		0.120	0.134	0.368	
	Prop. of White	0.549	0.192	0.004	**	0.513	0.202	0.011	*	−0.281	0.107	0.009	**
	Prop. of Asian	0.258	0.241	0.284		−0.071	0.257	0.783		−0.256	0.125	0.041	*
	Median Income	0.001	0.001	0.099	.	−0.001	0.001	0.177		−0.001	0.001	0.052	.
	Prop. of College Degree	0.990	0.228	0.000	***	0.767	0.240	0.001	**	−0.077	0.136	0.572	
	Prop. of Utilities Jobs	−0.066	0.114	0.560		0.002	0.114	0.983		0.036	0.067	0.588	
	Prop. of Goods-Product Jobs	−0.161	0.171	0.347		0.025	0.172	0.886		0.081	0.094	0.388	
	Population Density	0.003	0.001	0.031	*	0.004	0.001	0.001	***	0.001	0.001	0.114	
	Job Density	0.002	0.006	0.716		−0.008	0.006	0.161		−0.003	0.004	0.470	
	Prop. of Car	−0.825	0.218	0.000	***	−0.661	0.224	0.003	**	0.097	0.127	0.446	
Land use	Prop. of Commercial	0.313	0.429	0.465		−0.050	0.454	0.913		−0.134	0.267	0.616	
	Prop. of Industrial	−1.517	0.629	0.016	*	−1.380	0.669	0.039	*	0.107	0.352	0.762	
	Prop. of Institutional	−0.551	0.338	0.103		−0.158	0.357	0.658		0.086	0.202	0.671	
	Prop. of Open space	0.538	0.288	0.062	.	1.185	0.303	0.000	***	0.603	0.174	0.001	***
	Prop. of Residential	−0.659	0.348	0.058	.	0.714	0.375	0.057	.	0.765	0.211	0.000	***
Transportation features	Road Density	0.005	0.002	0.027	*	0.004	0.002	0.089	.	0.000	0.001	0.786	
	Bike Route Density	0.028	0.013	0.028	*	0.035	0.013	0.008	**	0.004	0.008	0.622	
	Transit Ridership	0.004	0.002	0.015	*	−0.001	0.002	0.656		0.002	0.001	0.061	.
Station characteristics	Distance to Nearest Bike Station	−0.810	0.345	0.019	*	0.428	0.355	0.229		0.623	0.191	0.001	**
	Capacity	0.046	0.003	0.000	***	0.025	0.003	0.000	***	−0.010	0.002	0.000	***
COVID-19 features	No. of Cases					−0.876	0.160	0.000	***	−0.072	0.080	0.370	
Smooth terms													
		e.d.f	Chi.sq	P-value		e.d.f	Chi.sq	P-value		e.d.f	F	P-value	
	ti (latitude, longitude)	6.178	72.448	0.000	***	9.481	122.953	0.000	***	4.276	1.032	0.354	
	Model fit												
	R-sq. (adj)	0.527				0.610				0.400			
	Deviance explained	81.10%				74.80%				43.40%			

a. Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1. Variables with *P*-values smaller than 0.1 are considered as statistically significant.
b. Since the cumulative relative change value is negative, a negative coefficient indicates that a larger independent variable leads to a lower (more negative) relative change, i.e., a greater decrease.

in areas with higher proportions of open space and residential lands. Such findings are intuitive since stay-at-home orders restrict individual movement scope to their home, contributing to the increase in human movement near residential lands. Also, since more bike-sharing trips are generated for exercise/leisure during the pandemic, the open spaces, like parks and green spaces, would become the more attractive spots for riders.

For transportation features, road density and bike route density both present significant positive signs in Model I and II, which is consistent with prior studies (Chen et al., 2018; Noland et al., 2016; Wang and Chen, 2020). The transit ridership shows a slightly significant positive relationship in Model I, and such a relationship attenuates during the pandemic. Meanwhile, a significant positive relationship is observed in Model III. In sum, *regions with higher transit ridership generate more bike-sharing trips during regular periods and decrease relatively less during the pandemic*. One explanation is that the relationship between bike-sharing and transit has changed from complement (Faghih-Imani and Eluru, 2015) to substitute (Pase et al., 2020) due to the pandemic's outbreak. During regular periods, a complementary relationship indicates bike-sharing pickups positively correlate with transit ridership. During the pandemic, the high risk of being infected in the public environment may push some transit passengers to shift to bike-sharing. Thus, a lower relative decrease in bike-sharing usage is observed in areas with more transit ridership.

Among station characteristics, the distance to the nearest bike-sharing station presents a significant negative relationship in Model I. However, such a relationship disappears in Model II. Meanwhile, a significant positive relationship is observed in Model III. Together, these findings indicate that *compact bike-sharing station clusters generate more*

trips during regular periods but suffer more relative loss during the pandemic. We argue this may because stations are distributed more compact near the city center but more scattered in suburban areas, while regions near the city center present a noticeable "more generation more loss" pattern in travel demand, as shown in Figs. 4 and 5.

Similarly, the coefficient of the number of docks in the bike-sharing station shows a significant positive sign in Model I and II and shows a significant negative sign in Model III. Such difference suggests *larger stations generate more trips in both periods but suffer a more significant relative trip loss during the pandemic*. It is intuitive since larger stations imply more available bikes and are always located in areas with higher potential travel demand (Faghih-Imani and Eluru, 2015, 2016). It is worth mentioning we should be careful to make any causal inference here considering the endogeneity bias when modeling the relationship between shared-bike trips and station characteristics (Faghih-Imani and Eluru, 2016; Wang and Chen, 2020). Finally, for the number of COVID-19 cases, only a significant negative relationship is observed in Model II, meaning *areas with more cases generate fewer trips during the pandemic*. The panic effect may explain the negative sign to some extent, as residents would perceive higher risk of contagion in areas with more cases. In addition, considering people of non-white and with low-income are disproportionately susceptible to COVID-19 infections due to the higher proportions of occupying frontline essential services and the prevalence of comorbidities (Hooper et al., 2020), the negative correlation here might also be explained by the fact that bike-sharing is relatively less used by those underprivileged populations.

4.4. Results of nonlinear interactions

Results of nonlinear interactions between time and independent variables with the cumulative relative change as the dependent variable are shown in Fig. 7. For each subplot, the horizontal axis represents the time index measured in the day, while the vertical axis represents the independent variable of interest. The contour and heatmap represent the interaction (i.e., the effects on cumulative relative change) given the independent variable and time. Compared with cross-sectional analysis, longitudinal models can capture more time-varying information regarding the relationship of interest in the study period. In particular, model III is to fit the cross-section of Fig. 5 on July 31st, 2020. Thus, we can find high consistency between results in Model III and the cross-sectional pattern on July 31st, 2020 in Fig. 5.

Horizontally, all subfigures present a trend varying like "light brown (*Time Index* < −10) - dark brown (*Time Index* ∈ [−10,10]) - light blue (*Time Index* ∈ [10,40])) - dark blue (*Time Index* ∈ [40,120]) - light blue (*Time Index* > 120)", which highly aligns with the temporal pattern of cumulative relative change shown in Fig. 2. This indicates that GAMMs successfully capture the nonlinear temporal patterns of the cumulative relative change in bike-sharing usage. Vertically, different subfigures present different trends, and the trend also varies across different periods. In particular, we are interested in changing patterns during the *pre-pandemic period* (*Time Index* ∈ [−10,10]) and *post-pandemic period* (*Time Index* ∈ [40,120]), as well as the time when the cycling mobility starts to drop and recover. The take-away information is summarized in Table 6.

For socio-demographics, the proportion of white residents present a similar pattern with the proportion of Asian. However, the latter shows a slightly less relative decrease and a more relative increase given the same period. Both white and Asian present an opposite pattern with black. Specifically, bike-sharing usage in regions with more white, more Asian, and less black shows less relative increase during the pre-pandemic period and more relative decrease during the post-pandemic period. Such regions also present an earlier start-to-drop time and a later start-to-recover time. In a nutshell, *regions with more white and Asian residents become less dependent on bike-sharing during the pandemic, while regions with more black residents become more dependent*. However, the median household income presents a slightly different pattern like a "flash mob": *bike-sharing usage in high-income areas presents greater relative increase during the pre-pandemic period and then reverses to greater relative decrease during the post-pandemic period*. Similar findings are also documented in prior studies (Weill et al., 2020) being describing as "*a reversal in the ordering of social distancing by income*". Many high-income regions are near the city center or commercial lands, explaining the pre-pandemic sharp increase in high-income areas. People may come in great numbers to these areas to stock up goods for possible lockdown before the pandemic. Thus, the sharp increase in pickups may not be solely induced by residents but also by external visitors (Pase et al., 2020).

Regarding land use, the proportion of open space and the proportion of residential land present similar patterns. Regions with more open space and residential lands present more relative increase during the pre-pandemic period and smaller relative decrease during the post-pandemic period. Such regions also present a later start-to-drop time and an earlier start-to-recover time. Transit ridership does not present a substantial relationship with the relative change before the pandemic. However, during the post-pandemic period, regions with more transit ridership exhibit smaller relative decrease in bike-sharing usage, which can be sourced to the newly-formed substitute relationship between bike-sharing and transit.

Last, for station characteristics, stations with longer distances to the nearby bike-sharing station present more relative increase during the pre-pandemic period and present less relative decrease during the post-pandemic period. This indicates that isolated stations become more critical in the bike-sharing system under the pandemic. Stations near the city center and stations with more docks present more relative increase during the pre-pandemic period and show more relative decrease during the post-pandemic period (somewhat like stations located in high-income areas). Also, these stations present a later start-to-drop time and start-to-recover time. A similar phenomenon is found in bike-sharing systems in China, where city centers are the most impacted area during and shortly after the pandemic (Chai et al., 2020).

5. Discussion, conclusion, and limitation

Leveraging two years of daily trips in the Divvy bike-sharing system in Chicago and using a set of cross-sectional and longitudinal modeling, this study examined the spatiotemporal changing patterns of bike-sharing usage during the COVID-19, compared the bike-sharing evolution trends with other modes of transport, explored the socio-economic disparities, visualized the nonlinear temporal interactions, and quantified the underlying mechanisms. Findings show that temporal patterns of bike-sharing usage vary across different regions, wherein socio-demographics like median income and race, land use feature like open space and residential lands, transit ridership, and station characteristics like spatial compactness and station capacity play the most critical roles. We summarized the main conclusions as follows:

1) By descriptive analysis of trip features, we found during the pandemic, the proportion of member trips vastly decreases while the proportion of casual trips dramatically increases. The average trip distance and trip duration increase, and the trip purposes change from "more commuting" to "more leisure". Regarding network structure, we found the pandemic dramatically curtailed the strength of connection and contracted the complexity of the bike-sharing network structure.

2) By comparing bike-sharing with different modes of transport including driving, walking, transit, and total travel, we noticed a substantial disproportion in mobility fall and rebound. Bike-sharing is the most robust and resilient option under the shock of the pandemic, with the highest recovery speed and greatest recovery magnitude. On the contrary, transit bears the hardest hit, losing the most travels and recovering remarkably tardily.

3) By modeling the absolute average pickups in regular periods (i.e., 2019), we found bike-sharing is more prevalent among regions with more white, high-income, and educated residents, with higher population density, and with fewer residents commuting by private cars. Industrial land presents a negative relationship with bike-sharing usage, while open space presents a positive relationship. Higher road density, denser bike routes, and greater transit ridership all positively correlate with bike-sharing usage. For station characteristics, compact spatial distribution and large station capacity both help promote bike-sharing usage.

4) By analyzing the cumulative relative change in bike-sharing usage across the pandemic, we documented the average trend follows an "increase-decrease-rebound" pattern. By modeling, we found regions with more white, Asian, and less black residents become less dependent on bike-sharing during the pandemic, starting to drop earlier, decreasing relatively more, and starting to recover later. We also found open space and residential lands present less relative decrease and earlier start-to-recover time. As for transit, we found the relationship between bike-sharing and transit shifts from complement to substitute during the pandemic. In addition, we found stations near the city center, with more docks, or located in high-income areas present a "flash mob" pattern: bike-sharing usage in these stations present more relative increase when the pandemic is imminent but shift to more relative decrease during the pandemic. These stations also have a delayed start-to-drop and start-to-recover time. Last, we found isolated stations become more important in the bike-sharing system under the pandemic, showing more relative pre-pandemic increase and less relative post-pandemic decrease.
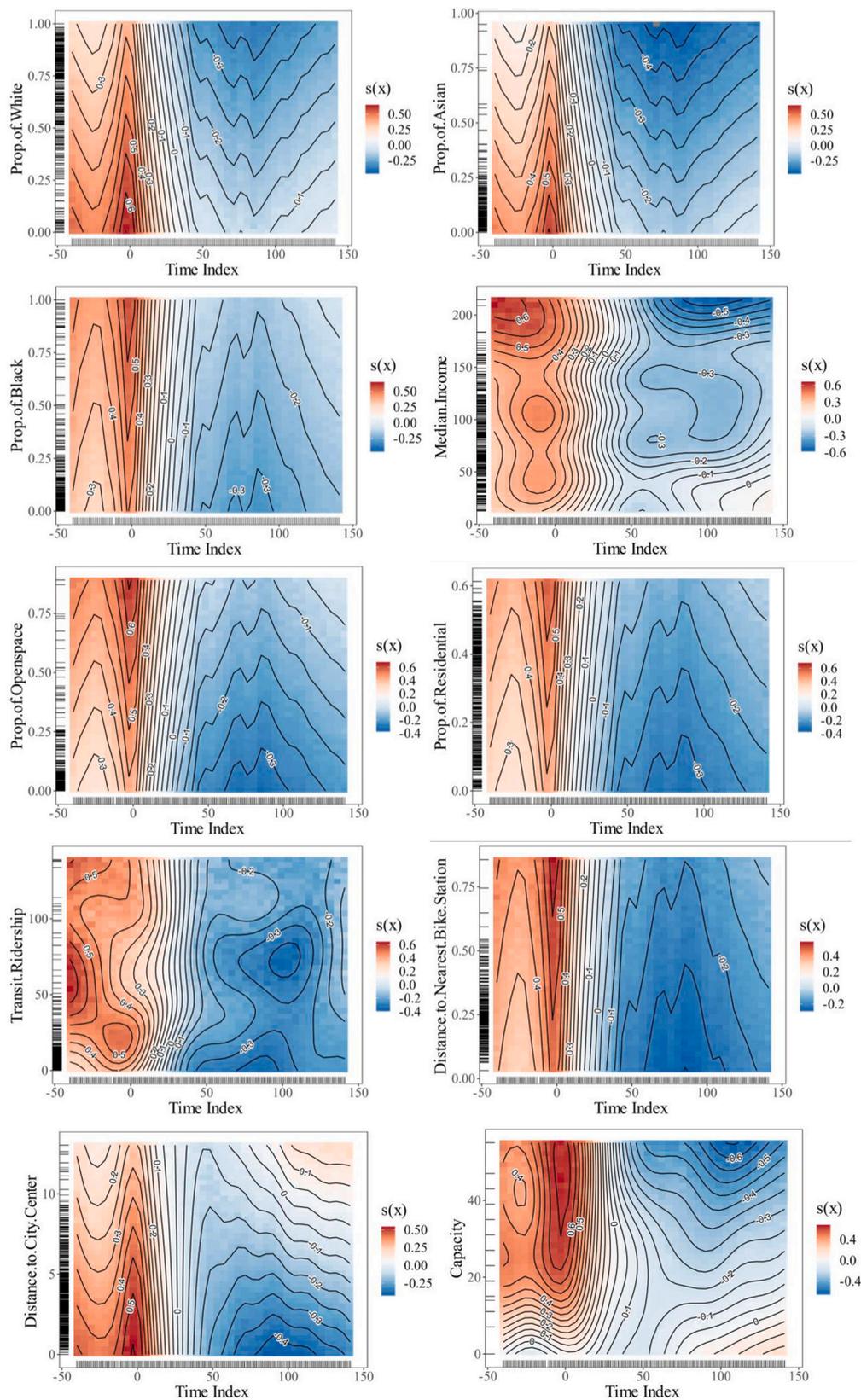
Fig. 7. Nonlinear interactions between time index and different independent variables of interest regarding the cumulative relative changes.
Note: a) All models have controlled weather conditions (temperature and rainfall), holidays, time-series seasonality (weekly and monthly), and other linear fixed effects except for the variable of interest. b) Only variables with statistically significant interaction with time index (i.e. *P*-value <0.1) are plotted. c) The horizontal axis varies from February 1st, 2020 to July 31st, 2020. March 11th, 2020 is set as Day 0, and days with negative indexes represent days earlier than March 11th, 2020. d) For some comparable pairs of variables, i.e., *Prop. of White* vs. *Prop. of Asian* vs. *Prop. of Black*, *Prop. of Openspace* vs. *Prop. of Residential*, the scale of color bar is set as the same.

Table 6
Summary of nonlinear interactions.

Independent Variable	Pre-pandemic (Time Index ∈ [−10,10])	Time Start to Drop	Post-pandemic (Time Index ∈ [40,120])	Time Start to Recovery
Prop. of White	Less increase	Earlier	More decrease	Later
Prop. of Asian	Less increase	Earlier	More decrease	Later
Prop. of Black	More increase	Later	Less decrease	Earlier
Median Income	More increase	Later	More decrease	Later
Prop. of Open space	More increase	Later	Less decrease	Earlier
Prop. of Residential	More increase	Later	Less decrease	Earlier
Transit Ridership	–	–	Less decrease	Earlier
Distance to Nearest Bike Station	More increase	Later	Less decrease	Earlier
Distance to City Center	Less increase	Earlier	Less decrease	Earlier
Capacity	More increase	Later	More decrease	Later

Findings provide a timely understanding of bike-sharing usage trends and offer suggestions on how different stakeholders should respond to the unprecedented change. First, the local government should consider the vital role of bike-sharing in the transportation system during the pandemic (Pase et al., 2020). While public transportations are the signature of an efficient urban transport system, alternative transport modes, such as bikes, are required as a more feasible and robust solution to maintain social distancing. During a pandemic, the fear of overcrowding is worsened by the risk of contagion. Bike-sharing can play the role of ameliorating factors during disruptive events that satisfy urban residents' travel needs. Also, cycling can serve as an excellent outdoor exercise for individuals to keep fit and healthy, which is particularly important to protect themselves from the virus. Moreover, it provides a lifestyle change option for the more environmentally sustainable city facing climate change after the pandemic. Thus, the local government should encourage those who still need to travel to consider use bike-sharing rather than transit if possible. For those staying at home for a long time, cycling regularly also helps them reduce the risk of health problems associated with a sedentary lifestyle and boost their immune system against the COVID-19. Second, this paper suggests a spatial disparity in bike-sharing demand during the pandemic, which would help bike-sharing operators adjust their services better and ensure people's cycling needs are well served. We suggest adjusting the number of shared bikes based on socio-economic characteristics and spatial needs. One example could be relocating bikes from regions with a lower concentration of vulnerable people to those areas with more vulnerable people. Such adjustment not only helps bike-sharing programs remain a higher turnover rate but also help more people away from the overcrowding transit, keep social distancing, and finally contain the spread of the virus. It is also worth mention that bike-sharing still belongs to a mode of public transport. Considering the virus's aerosol and surface stability (Van Doremalen et al., 2020), it is necessary to institute additional cleaning and disinfection procedures consistently, correctly, and more frequently to protect the bike-sharing riders. Lastly, the deep socio-economic inequities deserve more attention. This study adds to the growing body of evidence suggesting that the burden of the pandemic is spread unevenly across demographic groups (Bliss et al., 2020; Bonaccorsi et al., 2020; Brough et al., 2020; De Vos, 2020; Hu and Chen, 2021; Pase et al., 2020; Sy et al., 2020; Wilbur et al., 2020). The state and local agencies should focus more on underserved and vulnerable populations to address challenges in following the stay-at-home orders and the new social-distancing norm. For example, the local government should enhance the wage of essential jobs, allocate more subsidies to essential workers, and estimate the changing travel demand in a timely matter to better allocate resources.

Several limitations are recognized. First, this study mixes casual trips

and member trips when building models. Considering the difference in travel behavior and travel purpose between bike-sharing casual and member (Wang and Lindsey, 2019), it would be interesting to analyze the trips separated by user types. Second, the potential endogeneity of bike-sharing station characteristics is likely to over-estimate the impact of bike-sharing infrastructure in statistical inference. Further studies should consider employing some specific models like Two-Stage least squares (2SLS) regression to address the endogeneity (Faghih-Imani and Eluru, 2016). Last, findings from this study are region-specific since only one city is analyzed. The verification for more cases is warranted to test the generalizability of the findings.

Declaration of Competing Interest

The Authors declare no conflict of interests.

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