Getting Back on Track: Understanding COVID-19 Impact on Urban Mobility and Segregation with Location Service Data

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Abstract

Understanding the impact of COVID-19 on urban life rhythms is crucial for accelerating the return-to-normal progress and envisioning more resilient and inclusive cities. While previous studies either depended on small-scale surveys or focused on the response to initial lockdowns, this paper uses large-scale location service data to systematically analyze the urban mobility behavior changes across three distinct phases of the pandemic, *i.e.*, *pre-pandemic*, *lockdown*, and *reopen*. Our analyses reveal two typical patterns that govern the mobility behavior changes in most urban venues: daily life-centered urban venues go through smaller mobility drops during the lockdown and more rapid recovery after reopening, while work-centered urban venues suffer from more significant mobility drops that are likely to persist even after reopening. Such mobility behavior changes exert deeper impacts on the underlying social fabric, where the level of mobility reduction is positively correlated with the experienced segregation at that urban venue. Therefore, urban venues undergoing more mobility reduction are also more filled with people from homogeneous socio-demographic backgrounds. Moreover, mobility behavior changes display significant heterogeneity across geographical regions, which can be largely explained by the partisan inclination at the state level. Our study shows the vast potential of location service data in deriving a timely and comprehensive understanding of the social dynamic in urban space, which is valuable for informing the gradual transition back to the normal lifestyle in a "post-pandemic era".

Introduction

With more than 55% of the world's population living in cities (UN 2018), it is of paramount importance to understand how cities react to and recover from the COVID-19 crisis. In this unprecedented pandemic, various mobility restriction policies have been implemented to curb virus spread, including stay-at-home orders (Nivette et al. 2021) and banning certain indoor businessess[1]. These restrictions cause abrupt mobility reduction which poses serious challenges to the operation of urban systems (Tirachini and Cats 2020; Lutu et al. 2020) and even spills impact on online social network usage (Li et al. 2021b). More importantly, as Jane Jacobs famously argued that urban mobility is the underlying social fiber in cities that holds community social structures together through "cross-use of space" (Jacobs 1961), it is crucial to understand how mobility reduction affects social segregation at urban venues.

While considerable research attention has been drawn, most previous studies used survey questionnaires or field experiments to examine urban mobility, including park access (Zhang et al. 2022), restaurant patronage (Palacios et al. 2022) and teleworking (Conway et al. 2020). These studies are often limited by the scalability of research methods and only focus on a specific aspect of urban mobility. As online service data are becoming increasingly available as a tool to facilitate understanding of real-world social phenomena (Zhang, Lin, and Pelechrinis 2016; Zhang and Pelechrinis 2014; Cranshaw et al. 2012), several studies leveraged social media check-ins (Han et al. 2021), bike-sharing data (Li et al. 2021a) and mobile phone data (Nouvellet et al. 2021) to sense mobility changes at scale, but they zoned in on the response to the initial lockdown in 2020, overlooking the long-term behavior changes in the following years, especially when vaccines have been widely administered and daily life is getting back on track. More importantly, they failed to interpret the implications of mobility change for the social dynamics in urban space.

Different from previous research, this study aims to derive a comprehensive picture of urban mobility change at scale across multiple phases of the COVID-19 pandemic, through the lens of the following three research questions:

RQ1: Can pervasively collected location service data reveal meaningful patterns of mobility behavior changes during the COVID-19 crisis?

RQ2: How do the mobility behavior changes affect the social inclusiveness in urban space?

RQ3: Are the mobility behavior changes consistent across geographical regions?

To answer these questions, we propose a data-driven analytic framework with the following key designs. First, we leverage a large-scale location service dataset that records 35 billion visits to 2.08 million urban venues in the United States from March 2019 to February 2022. The dataset enables longitudinal analysis to systematically compare the

[1]https://www.usatoday.com/storytelling/coronavirus-reopening-america-map/

mobility behavior in *pre-pandemic*, *lockdown* and *reopening* periods across all 50 states. Second, we derive a conceptual map based on the relative visitation drop during the lockdown period and the relative visitation recovery in the reopening period to reveal the universal patterns among heterogeneous urban venues. Third, we design a visitation segregation index (VSI) that quantifies the experienced segregation in a specific urban venue as the likelihood of visitors coming from similar socio-demographic backgrounds, and evaluate its association with the change in mobility behavior. Finally, we investigate the geographic differences in mobility change patterns with clustering analyses, and further uncover the links between mobility behavior change and local governing policies.

Our analysis under the proposed framework yields several insightful observations. First, most urban venues exhibit a universal pattern, i.e., the relative mobility level at the reopening period scales linearly with the relative mobility level at the lockdown period, which indicates that urban venues suffering from large mobility drops are likely to experience persistent avoidance even after reopening. Second, closer inspection reveals two dominant types, i.e., daily life-related and work-related patterns, while venues belonging to *Parks*, *Information* and *Educational* categories form three outliers due mainly to their unique urban functions. Third, we find a positive correlation between the experienced income/racial segregation and the level of mobility reduction, indicating that urban venues enduring more mobility drop during lockdowns are more susceptible to social segregation. Finally, the differences in urban mobility change can be largely explained by the political inclination of the residential states. Specifically, the two main clusters of mobility change patterns can be predicted with 81.25% accuracy by partisan inclination, where the Republican-leaning states generally have a higher relative mobility level during both lockdown and reopening periods.

In summary, we make the following contributions:

1. We propose a data-driven analytic framework to comprehensively understand the impact of COVID-19 on urban mobility patterns at scale, emphasizing the huge potential of exploring the cyber-physical nexus to investigate real-world social phenomena.
2. We establish a conceptual map to discern between heterogeneous patterns of mobility change associated with different types of urban venues, and dig into the underlying reasons regarding distinct urban functions.
3. We find a positive correlation between the experienced segregation and mobility reduction at urban venues, which suggests maintaining urban mobility is indeed important to healthy neighborhood social fabrics.
4. We show that the main patterns in state-level urban mobility change can be accurately predicted by partisan inclination, which provides a potential mechanism to explain the different responses between states.

Related Work

We categorize related works along three dimensions.

Evaluating the impact of COVID-19 on urban venue accessibility. A variety of works have provided insights on how the COVID-19 pandemic impacts urban systems, especially the accessibility of urban venues, which can be classified into two categories based on the research method. **(1) Survey-based.** Zhang et al. (2022) conduct a questionnaire survey on the changes in park visits change, and find that higher epidemic risk leads to lower park accessibility and greater inequality in park access. Conway et al. (2020) conduct a survey among highly-educated US residents on the impacts of COVID-19 on work and life patterns, and discover a decreasing demand in restaurant patronage and an increasing hope to continue teleworking after the pandemic. Albeit offering valuable insights, survey-based studies are inevitably influenced by self-report bias and constrained by sample sizes, and thus unable to provide a comprehensive picture of the mobility changes. Different from them, we base our analysis on large-scale mobility data collected from online location services, which contains rich and fine-grained information about people's real-world movements. **(2) Sensing-based.** Han et al. (2021) utilize check-in data to identify several "early bird" categories that exhibit visit drops before the city lockdown. Li et al. (2021a) use bike-sharing data to study inter-city mobility during lockdowns and find a decrease in the share of workplace visits but an increase in that of park and grocery store visits. These works overcome the limitation of self-report bias, but did not provide a systematic analysis of mobility changes across different phases of the pandemic. Different from them, we jointly analyze the mobility patterns in three phases of the COVID-19 pandemic, and conceptualize a systematic framework to classify various urban venues by mobility change patterns.

Leveraging online location service data to understand real-world social phenomena. Digital traces collected from online service platforms, including check-in, geo-tagging and passive geo-positioning data, provide fine-grained information about human activities (Cranshaw et al. 2010; Cho, Myers, and Leskovec 2011), which have huge potential to uncover the principles governing physical activity patterns. Using such data, researchers discovered latent structures in urban transition flows (Zhang, Lin, and Pelechrinis 2016), revealed the mechanisms behind spatial homophily (Zhang and Pelechrinis 2014), and renovated notions of activity areas beyond traditional municipal boundaries (Cranshaw et al. 2012). This line of works derives critical insights into the emergence of collective behavioral patterns from individual movements. Complementary to these works, we provide insights into the change of human mobility patterns during different phases of a pandemic crisis. Online service data also shed light on solving various real-world social problems, e.g., estimating urban inequality (Ganter, Toetzke, and Feuerriegel 2022), predicting crime concentrations (Kadar et al. 2020; Rumi, Shao, and Salim 2020), and tracking public concerns (Wang and Taylor 2018). In this work, we reveal the impact of COVID-19 on experienced segregation which is an important aspect of neighborhood social fabrics.

Urban mobility and experienced segregation. A long history of research has been focused on residential segregation in urban spaces, where people of the same racial/ethnic backgrounds and similar socioeconomic status tend to reside closer to each other and thus form distinct neighborhoods

(Charles 2003; Taeuber and Taeuber 2008; Lichter, Parisi, and De Valk 2016). However, such static segregation metrics are insufficient in reflecting people's daily experience of social isolation when traveling in urban environments. Thus, some recent studies propose a type of *de facto* segregation emerging from people's everyday mobility behavior, referred to as experienced segregation. Wang et al. (2018) utilize social media data to exhibit the persistent isolation between neighborhoods of different socioeconomic statuses despite long travel distances. Moro et al. (2021) use mobile phone positioning data to further reveal the association between individual visitation preferences and the experienced segregation in different kinds of places. However, existing works study the relationship between mobility and segregation in a single snapshot, without considering how changes in the former may bring about changes in the latter. Complementary to them, we use different phases of the COVID-19 pandemic to form a natural experiment, so that we can observe the changes in experienced segregation when substantial changes are imposed on urban mobility patterns.

Urban mobility and partisanship. Classic works on partisanship and mobility typically focus on long-term outcomes such as migration-induced geographical assortativity (Gimpel and Hui 2015; Tam Cho, Gimpel, and Hui 2013), and social mobility (Dancygier and Saunders 2006). More recent works turn to short-term physical mobility, analyzing its connection with people's political inclinations. It is found that partisan differences are associated with people's willingness to reduce mobility and adopt other prevention measures (Clinton et al. 2021; Bruine de Bruin, Saw, and Goldman 2020). Such a relation is mediated by a range of subjective factors, including perceived health risk, perceived effectiveness of prevention measures, and optimism about a forthcoming end of the pandemic (Stroebe et al. 2021; Freira et al. 2021). While these studies base their results on questionnaires for individuals, we provide a holistic view of such behavior gaps throughout multiple pandemic phases by directly looking into human mobility data.

Data Description

In this study, we mainly use three types of data, i.e., POI data, mobility data, and demographic data. For **POI data**, we leverage Safegraph's Places dataset[2], which is collected from open-source web domains and publicly available APIs. It contains detailed information about a POI's name, address, industrial type, etc. For **mobility data**, we leverage Safegraph's Patterns dataset[3], which is a large-scale dataset that records visits to POIs in the US from online applications with location services. It records the number of visits paid to each POI by residents of each CBG, aggregated on a monthly basis, along with supplementary statistics such as popularity by week and by hour. Although this dataset is a sample of all happened activities, existing works (Kang et al. 2020; Brelsford et al. 2022) have validated its consistency with other datasets and representativeness of the real-world situation. To account for uneven sampling across CBGs, we follow the common practice (Chang et al. 2021) to reweight POI visitations according to the ratio between the number of devices residing in each CBG to the corresponding CBG. We select the POIs located in urbanized areas according to the rural-urban classification scheme provided by the U.S. Department of Agriculture[4], and further group POIs into industrial categories based on the North American Industry Classification System (NAICS)[5]. Specifically, we focus on the following 15 representative POI categories: *Parks*, *Educational*, *Information*, *Retail*, *Health Care*, *Recreation*, *Hospitality*, *Construction*, *Manufacturing*, *Wholesale*, *Transportation*, *Finance*, *Professional*, *Community Services*, and *Public Admin*. We summarize the semantic meanings and statistics of POI categories in Table 1.

The monthly visitation frequencies are shown in Figure 1. We observe that the overall visitation frequency dropped significantly after Feb. 2020, when the COVID-19 pandemic started to surge in the US. After remaining low for months, the overall visitation frequency began to rebound and has remained on a higher level since May 2021, which is consistent with the timeline of reopening[6]. Based on these observations, we take mobility data from three distinct phases of the pandemic for comparative analysis. The *pre-pandemic* phase is represented by Jan. 2020 - Feb. 2020, before the WHO declaration of COVID-19 as a pandemic (Cucinotta and Vanelli 2020). The *lockdown* phase is represented by Jan. 2021 - Feb. 2021, when national and local authorities put into effect a series of COVID-related restriction policies in face of the surging numbers of COVID-19 cases and deaths. The *reopening* phase is represented by Jan. 2022 - Feb. 2022, when most parts of the country have lifted restrictions and gone back to business as usual[7].

To link mobility behavior to visitor attributes, we obtain **demographic data** from the 2019 American Community Survey (ACS) 5-year Estimates, which record demographic compositions of census block groups (CBGs). As the smallest geographical unit with publicly-released demographic statistics and a typical population between 600 and 3,000, CBGs provide a suitable scale for analyzing socioeconomic differences. We divide CBGs into four income quartiles according to median household income, and four race quartiles according to the percentage of residents belonging to racial/ethnic minorities (Van Voorhees et al. 2007), and use them to quantify experienced segregation in venue visitation.

Methods

Profiling Urban Mobility Behavior Changes

We denote the visitation frequency in the *pre-pandemic*, *lockdown*, and *reopening* phases as F_p, F_l, and F_r, respectively. For each POI category, we depict the changes in the

[2]https://docs.safegraph.com/docs/places

[3]https://docs.safegraph.com/docs/monthly-patterns

[4]https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/

[5]https://www.census.gov/naics/

[6]https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html

[7]https://equityschoolplus.jhu.edu/reopening-policy-tracker

POI Category	Semantics	# POIs	# Visits
Parks	Museums; Historical Sites; Zoos and Botanical Gardens; Nature Parks; etc	60,331	152,667,649
Educational	Elementary and Secondary Schools; Colleges, Universities, and Professional Schools; etc.	102,653	364,937,602
Information	Telecommunications; Data Processing, Hosting, and Related Services; etc.	19,781	16,491,829
Retail	Food and Beverage Stores; General Merchandise Stores; Miscellaneous Store Retailers; Gasoline Stations; Clothing Stores; etc.	531,754	975,684,932
Health Care	Ambulatory Health Care Services; Hospitals; Residential Care Facilities; etc.	366,497	308,464,684
Recreation	Performing Arts Companies; Spectator Sports; Gambling Industries; etc.	74,644	164,789,069
Hospitality	Traveler Accommodation; Rooming and Boarding Houses, Dormitories, and Workers' Camps; Drinking Places; Restaurants and Other Eating Places; etc.	434,291	822,447,845
Construction	Construction of Buildings; Heavy and Civil Engineering Construction; etc.	12,281	6,544,109
Manufacturing	Food Manufacturing; Apparel Manufacturing; Chemical Manufacturing; etc.	28,479	18,459,126
Wholesale	Durable Goods Wholesalers; Nondurable Goods Wholesalers	22,855	13,229,292
Transportation	Rail Transportation; Water Transportation; Transit and Ground Passenger Transportation; Warehousing and Storage; etc.	25,520	26,215,835
Finance	Credit Intermediation and Related Activities; Insurance Carriers and Related Activities; Funds, Trusts, and Other Financial Vehicles; etc	73,678	26,110,228
Professional	Legal Services; Specialized Design Services; Computer Systems Design and Related Services; Scientific Research and Development Services; etc.	31,219	11,338,793
Community Services	Automotive Repair and Maintenance; Personal Care Services; Drycleaning and Laundry Services; Religious Organizations; etc.	276,702	110,717,492
Public Admin	Executive, Legislative, and Other General Government Support; Administration of Housing Programs, Urban Planning, and Community Development; etc.	21,472	18,774,791

Table 1: POI category semantics and statistics.

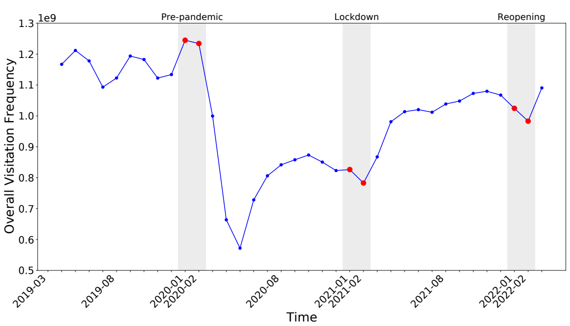


Figure 1: Monthly visitation frequency from 2019 to 2022.

associated visitation patterns with two metrics. First, we calculate the relative mobility level during COVID-19 lockdowns (denoted as M_l) as the change of visitation frequencies with respect to the *pre-pandemic* level:

$$M_l = \frac{F_l - F_p}{F_p}. \tag{1}$$

Second, we calculate the relative mobility level after reopening (denoted as M_r) as the change of visitation frequencies also with respect to the *pre-pandemic* phase:

$$M_r = \frac{F_r - F_p}{F_p}. \tag{2}$$

Taking these two metrics as Euclidean coordinates, we construct a two-dimensional conceptual map of POI categories, where proximity indicates similar patterns of mobility drop and recovery. We will elaborate on the conceptual map and the classification results in the Results section.

Measuring the Impact on Experienced Segregation

Seemingly free to move around in urban spaces, people from "mainstream" neighborhoods and disadvantaged neighborhoods still demonstrate considerably different patterns in venue visitation, due to both personal choices and capability to access important urban facilities. Such experienced segregation is ubiquitous, dynamic, and thus serves as a timely indicator of changes in individuals' social preferences, lifestyles, and the society's inclusiveness. To quantify the changes in experienced segregation throughout different phases of the COVID-19 pandemic, we devise a visitation segregation index (VSI) from the framework proposed by Moro et al. (2021). First, we divide CBGs into quartiles according to their different demographic characteristics, and assume people from the same CBG are associated with similar socioeconomic status, which is consistent with existing literature (Chang et al. 2021). As our mobility data records visits paid to each venue by people from each CBG, we aggregate CBGs within the same quartile to calculate the proportion of visitors from each quartile to a specific venue, denoted as p_i for the i-th quartile. Finally, we calculate the experienced segregation as the deviation of the realistic visitor composition from the ideal case where people from all quartiles evenly visit this venue. The resulting expression is shown below:

$$VSI = \frac{2}{3}\sum_{i=1}^{4}\left|p_i - \frac{1}{4}\right|. \tag{3}$$

Note that by adding a constant multiplier to the expression, we ensure that the value falls within $[0, 1]$. Specifically, if people from all quartiles visit a venue equally, we have $p_i = \frac{1}{4}$ for all i, and thus VSI= $\frac{2}{3}\sum_{i=1}^{4}\left|\frac{1}{4} - \frac{1}{4}\right|$=0, indicating the lowest segregation level. If visitors to a venue all come from the same quartile x, we have $p_x = 1$ while $p_i = 0$ for all $i \neq x$, which makes VSI$= \frac{2}{3} \cdot |1 - \frac{1}{4}| + 3 \cdot \frac{2}{3} \cdot \left|0 - \frac{1}{4}\right| = 1$, indicating the highest segregation level.

Specifically, we focus on two types of experienced segregation, i.e., income segregation and race segregation. Experienced income segregation is calculated based on population division by median household income, and experienced race segregation is calculated based on population division by the percentage of racial/ethnic minorities.

Discovering Patterns of Mobility Behavior Changes across Geographical Regions

To analyze the geographical patterns of mobility behavior changes in different states, we first characterize each state with a 30-dimensional vector, which is constructed by concatenating the state-level mobility change in the 15 categories during two phases: the *lockdown* phase and the *reopening* phase. On the feature vectors, we perform agglomerate clustering, a bottom-up approach that discovers clusters by successively merging data points. Specifically, we set the goal to be minimizing the average Euclidean distances between all data points belonging to any pair of clusters.

Results

Heterogeneous Mobility Behavior Changes in Urban Space (RQ1)

Taking the mobility level during COVID-19 lockdowns (M_l) and the mobility level after reopening (M_r) as coordinates, we obtain a conceptual map of POI categories, as shown in Fig. 2(a). Most of the categories (12 out of 15) are distributed along a straight line, except three. Each of these three categories can be traced to reasons acknowledged in literature or news report, which we will illustrate later. For the 12 ”mainstream” categories, Ordinary Least Squares (OLS) regression identifies this line as $M_r = M_l + 0.077$ (RMSE = 0.051, R^2 = 0.808), and all the 12 categories lie in its 99% confidence interval (CI). The high goodness-of-fit of the regression model validates the linear relationship between M_r and M_l, indicating a similar mobility elasticity shared by these 12 categories. In other words, the mobility recovery is not proportional to the mobility drop. Instead, venues with a smaller mobility drop can expect a larger relative mobility recovery, while great mobility drops are likely to persist through the whole pandemic. Taking *Retail* as an example, we observe that its mobility drop in *the lockdown* phase is very small, and thus its mobility level in the *reopening* phase has almost returned to the pre-pandemic level. By contrast, *Manufacturing* endures a large mobility drop, and its mobility in the *reopening* phase only restores to 40% of its pre-pandemic level.

By further analyzing the values along both axes and combining them with the semantics of these categories, we discover that these 12 categories are linearly separable by $M_r = -0.2$ in the two-dimensional space, resulting in two types that correspond to work-related venues and life-related venues, respectively. Specifically, Type 1 consists of 8 categories (*Construction*, *Wholesale*, *Finance*, *Public Admin*, *Professional*, *Manufacturing*, *Transportation*, and *Community Services*), all of which see a relatively small mobility recovery. As these categories are mainly working places, the visitations to the corresponding venues decreased due to the widely-adopted remote working policies aiming to reduce transmission risk. Albeit with certain mobility recovery, the magnitude of mobility remains clearly smaller than the pre-pandemic level, which indicates a likely-perpetual paradigm shift in people's working modes, i.e., from on-site to online. By contrast, Type 2 categories recover better towards the pre-pandemic level. This type consists of 4 categories (*Retail*, *Health Care*, *Recreation*, and *Hospitality*), which are essential businesses that support citizens' everyday needs. Thus, visitations to such venues display greater capability to resume normal.

Finally, each of the three remaining categories exhibits a distinct pattern of mobility change. Type 3 (*Information*) sees the most remarkable mobility drop and most petite mobility recovery, likely because many high-tech businesses in this category are highly capable of shifting to remote working. Type 4 (*Educational*) sees both a large mobility drop during the lockdown and a substantial mobility recovery after reopening. The main reason is that educational venues such as K-12 schools and universities are highly compliant with administrative policies, thus explicitly instructed to be closed during the most severe phase of the pandemic and gradually resume normal teaching afterwards[8]. Finally, Type 5 (*Parks*) turns out to be the only category that experiences no reduction but an increase in mobility during the lockdown. The main reason is that those who have gone through stay-at-home orders feel a greater need to socialize with other people. Since indoor venues are either closed or risky in transmitting viruses, many people turn to show greater passion for gardens, city parks, and other green open spaces (Curtis et al. 2021; Lu et al. 2021; Venter et al. 2020).

Next, we analyze how the proportion of visitations by POI category (Figure 3) changes through different phases of the pandemic. The top-5 categories receiving the most visitation before the pandemic are *Retail*, *Hospitality*, *Educational*, *Health Care*, and *Recreation*. During the *lockdown* phase, the top-4 categories remain the same, despite that *Health Care* and *Educational* exchange their positions. Meanwhile, *Parks* replaces *Recreation* to become the category receiving the fifth most visitations, consistent with our previous observation. After reopening, the top-5 categories resume the pre-pandemic order, although with different proportions of visitations. The restoration of the top-5 categories exhibits a certain level of resilience in the composition of visitation. The Chi-square independence test shows that the differences between category-wise visitations in different periods are statistically significant (lockdown & pre-pandemic: χ^2 = 21651683.3, df = 6, p = 0.00, reopen & pre-pandemic: χ^2 = 5867727.8, df = 6, p = 0.00, reopen & lockdown: χ^2 = 12943491.3, df = 6, p = 0.00).

These categories can be further divided into three tiers (Fig. 4): *Retail* is the top tier with the largest proportion of visitations; *Hospitality*, *Educational*, and *Health Care* con-

[8]https://equityschoolplus.jhu.edu/reopening-policy-tracker/

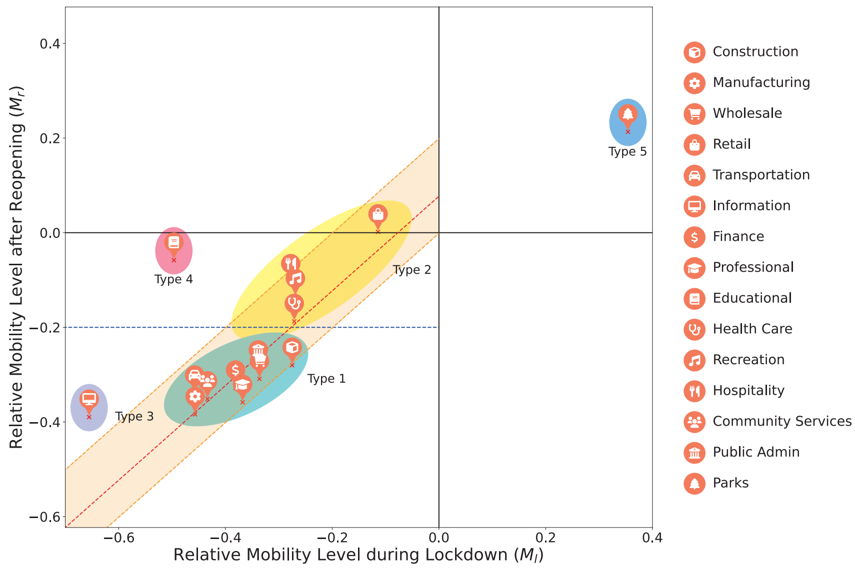


Figure 2: Conceptual map to classify urban venues based on mobility behavior changes. The colored circles denote five identified types of POI categories. The yellow linear area denotes the 99% CI of the regression performed on Type 1 and Type 2.

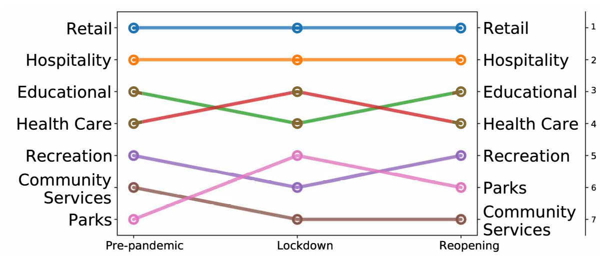


Figure 3: Categories with most visitation frequencies in three phases.

stitute the mid tier, and all the other categories make up the bottom tier. Comparing the *lockdown* phase with the *pre-pandemic* phase, we observe an increase in the proportion of visitations to both top-tier (from 29.7% to 34.9%) and bottom-tier (from 19.0% to 19.5%) categories, while mid-tier categories suffer a shrink (from 51.2% to 45.6%). We make sense of this observation by pointing out the relation between proportion expansion/shrinkage and the needs satisfied by different venues. The top-tier category of venues satisfy the common essential needs of urban residents, and the bottom-tier includes a wide range of services to satisfy diverse, highly-personalized needs. On the contrary, the mid-tier categories are either for satisfying optional needs or required to be closed during lockdowns, and thus the proportion of visits to such categories shrinks. The Chi-square independence test shows that the differences between category-wise visitations in different periods are statistically significant (lockdown & pre-pandemic: χ^2 = 12493730.6, df = 4, p = 0.00, reopen & pre-pandemic: χ^2 = 3176123.5, df = 4, p = 0.00, reopen & lockdown: χ^2 = 11655823.9, df = 4, p = 0.00). Later in the *reopening* phase, there is again a trend of returning to the pre-pandemic normal, with the proportion of visitations to the mid-tier rising to 50.1%. Our findings are aligned with Maslow's hierarchy of needs (McLeod 2007): during crises, people tend to focus more on fulfilling their basic physiological needs, and suppress higher-level needs including aesthetics, esteem and self-actualization. Such a change is transient and reversible, with higher-level needs naturally reviving as long as people feel their lower-level needs satisfied.

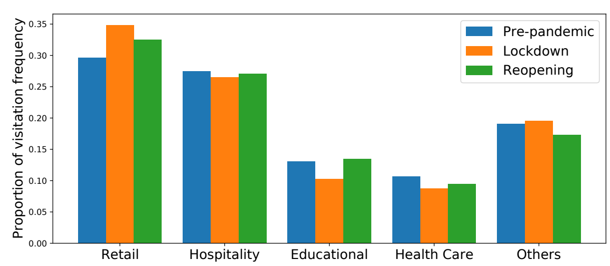


Figure 4: Proportion of visitation by venue category.

Third, we analyze how the weekday/weekend popularity of different venues changes with time (Fig. 5). First, certain patterns persist throughout different pandemic phases. For example, Type 2 venues have the greatest popularity on both weekdays and weekends before the pandemic, and the latter is even greater than the former by over 8 percentage points. In the *lockdown* phase, both popularity increase, making it still the most popular type. Moreover, we find that for different types of POIs and different periods of time, changes in weekday popularity are highly similar to those on weekends. The only exception is Type 2, whose weekday popularity decreases but weekend popularity increases in the *reopening* phase. This again indicates changes in residents' lifestyles brought by the pandemic. For example, people may now prefer a big purchase on weekends to store enough food and daily necessities, instead of dropping by convenience stores on the way to and back from work on weekdays. We also observe that the weekday and weekend popularity of Type 1 venues keeps decreasing during the lockdown and after reopening. This resonates with our observations from the conceptual map in Fig. 2 to indicate that changes in people's working paradigm reduces the need to visit Type 1 venues, which is likely to persist even after exit from the pandemic.

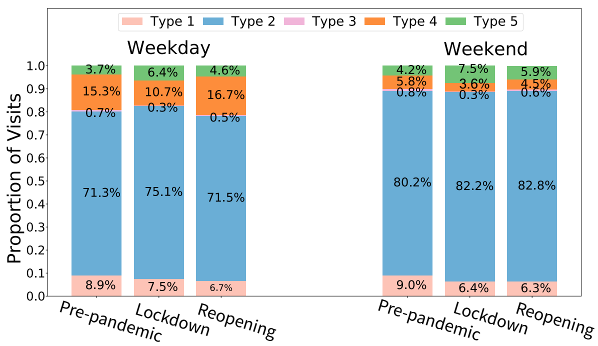


Figure 5: Popularity on weekdays/weekends by venue type.

Understanding the Implication for Experienced Segregation (RQ2)

In this section, we tease out how experienced segregation changes throughout different phases of the COVID-19 pandemic. As a preliminary, Fig. 6 shows different levels of income and race segregation associated with different categories of venues in the *pre-pandemic* phase. The highest level of segregation is observed in Type 1 venues (from *Construction* to *Public Admin*), while the lowest level is observed in Type 2 venues (from *Retail* to *Hospitality*). We also observe a clear correlation between experienced income segregation and experienced race segregation, which is reasonable as racial/ethnic minorities are more likely to be disadvantaged in economic status. Aggregating the changes in all POIs, we observe an increase in both income segregation ($\uparrow$ 7%) and race segregation ($\uparrow$ 5%) in the *lockdown* phase, alerting that different classes of people become more socially isolated in the pandemic, which may undermine the integration of the society. The trend is reversed to some extent in the *reopening* phase ($\downarrow$ 3% for income segregation and $\downarrow$ 2% for race segregation), but both kinds of experienced segregation are still above their pre-pandemic level, indicating the long-term impact of the pandemic. We perform paired samples t-tests to validate the statistical significance of differences. For income segregation, all three pairs of phases show statistical significance (lockdown & per-pandemic: t=-183.4, p=0.00, reopen & pre-pandemic: t=-94,7, p=0.00, reopen &lockdown: t=-95.5, p=0.00). Also, for race segregation, all three pairs of phases show statistical significance (lockdown & per-pandemic: t=-151.7, p=0.00, reopen & pre-pandemic: t=-82.3, p=0.00, reopen &lockdown: t=-74.5, p=0.00).

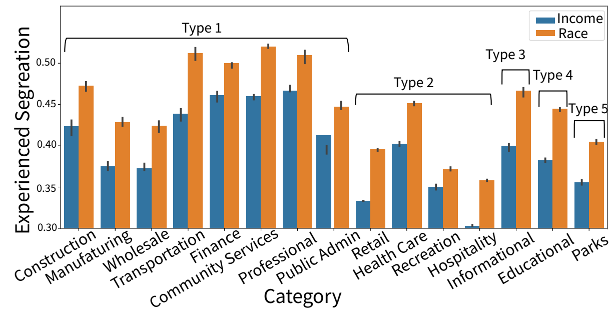
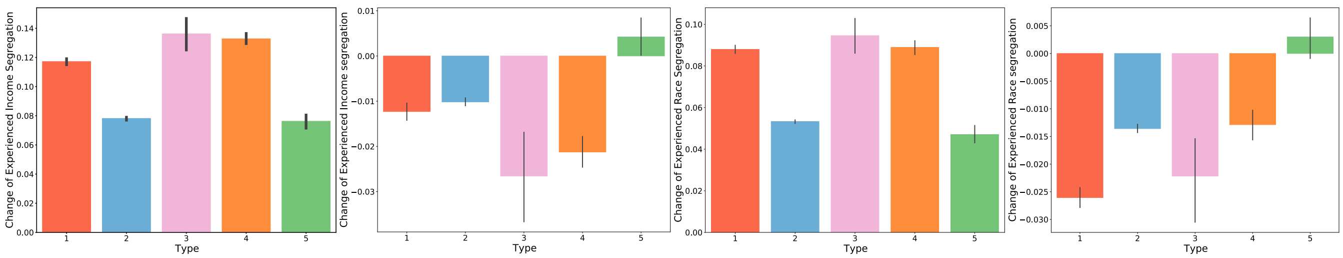


Figure 6: Experienced segregation in the *pre-pandemic* phase. Error bars denote within-category variation.

Next, we disaggregate the changes onto five venue types, and find different patterns of segregation change. Fig. 7(a)(c) show that during the *lockdown* phase, Type 3 (*Information*) venues see the greatest increase in both types of experienced segregation, followed by Type 4 (*Educational*), Type 1, Type 3 (*Information*) and Type 5 (*Parks*) venues. In the *reopening* phase, all types of venues except Type 5 (*Parks*) see a reduction in experienced segregation, with the greatest reduction in Type 3 venues, as shown in Fig. 7(b)(d).

Moreover, we discover an underlying connection between the change in experienced segregation and the magnitude of mobility drop/recovery in the corresponding phases. Recall that in the *lockdown* phase, Type 3, Type 4, Type 1 and Type 2 venues experience mobility drop from largest to smallest, while Type 5 venues see an increase (Fig. 2). For the first four types of venues, the more the mobility drops, the more the experienced segregation will increase. The main reason is that visitations to such venues are largely through "utilitarian" movements, i.e., people travelling purposefully to reach certain working or shopping places (Hunter et al. 2021). Such movements are generally associated with longer travel distances across neighborhoods, which contributes to a more homogeneous population mixing. By contrast, visitations to Type 5 belong to "leisure" movements, e.g., people walking around casually for relax or entertainment, which usually take place near their residential area. Moreover, the pandemic has strengthened this characteristic by increasing people's willingness to visit closer parks (Zhang et al. 2022). Thus, an increase of Type 5 visitations is likely to resonate with the existing residential segregation to strengthen the experienced segregation in Type 5 venues. As for the *reopening* phase, visitations to the first four types of venues recover to different extents, which corresponds to the reduction in experienced segregation. For Type 5 venues, since visitations keep increasing throughout the three phases, the experienced segregation does not change in a statistically significant manner compared to the *lockdown* phase.

To provide a finer-grained picture, we step down from the type level to the category level. For each pandemic phase and each type of segregation, we perform linear regression to predict the median segregation change of each venue category (y) using the median mobility change of



(a) Experienced income segregation, lockdown w.r.t. pre-pandemic.

(b) Experienced income segregation, reopening w.r.t. pre-pandemic.

(c) Experienced race segregation, lockdown w.r.t. pre-pandemic.

(d) Experienced race segregation, reopening w.r.t. pre-pandemic.

Figure 7: Changes of experienced segregation by venue type. Error bars denote within-type variance of experienced segregation.

each venue category (x). For the *lockdown* phase, we got $y = -0.1753x - 0.0260$ ($R^2 = 0.5613, p < 0.05$) for income segregation, and $y = -0.1083x - 0.0048$ ($R^2 = 0.3544, p < 0.05$) for race segregation. For the *reopening* phase, we got $y = -0.0905x - 0.0152$ ($R^2 = 0.4314, p < 0.05$) for income segregation, and $y = -0.0673x - 0.0019$ ($R^2 = 0.3158, p < 0.05$) for race segregation. We make two observations from the above regression results. First, albeit simple, such linear regression models can explain a considerable portion of the variability of segregation, indicating that the connection we identify between mobility change and segregation change is still robust on the category level. Second, the regression slope is steeper in the case of experienced income segregation (-0.1753 in the *lockdown* phase and -0.1083 in the *reopening* phase), compared to the experience race segregation (-0.0905 in the *lockdown* phase and -0.0673 in the *reopening* phase). As income segregation is more sensitive to mobility change, the widening gap between different income groups may raise more concerns during pandemic crises.

Analyzing the Differences between States (RQ3)

In this section, we analyze the geographical patterns of mobility change in 50 U.S. states. By clustering the feature vectors of the states (see the Methods section), we group the 50 states into 2 distinct clusters, leaving three states as "outliers". As shown in Fig. 8, Cluster-1 states are mainly located in the west and the east, while Cluster-2 states are mainly located in the central part of the country, displaying clear geographical patterns. Category-by-category comparison in Fig. 10, 11 shows that the two clusters differ significantly in the magnitude of mobility change: visitations to all categories of venues in Cluster 1 see a greater mobility drop during the *lockdown* phase, and remain lower in the *reopening* phase compared with their pre-pandemic level.

Moreover, we put the cluster map alongside the political inclination map derived from the 2020 U.S. presidential election statistics (Fig. 9), and observe a clear correspondence in between: Cluster 1 mainly consists of Democratic-leaning states, while Cluster 2 mainly consists of Republican-leaning states. In fact, even if we simply assign Democratic-leaning states to Cluster 1 and Republican-leaning states to Cluster 2, respectively, we are already able to achieve a hit rate of 81.25%. To rule out the confounding effects of income and race segregation, we perform regression analyses to predict state-level mobility change. Specifically, we compare two linear regression models. The first one only takes state-level political inclination as input, while the second one takes as input political inclination, race segregation and income segregation. In both *lockdown* and *reopen* phases, it turns out that state-level political inclination on its own already predicts mobility change pretty well ($R^2 = 0.557$ for *lockdown* and $R^2 = 0.419$ for *reopen*). Moreover, after taking into account income and race segregation, the state-level political inclination is still statistically significant ($p = 0.000$ for both *lockdown* and *reopen*) for the prediction of mobility change. From the above we note that political inclinations are significantly correlated to mobility change even when we control for differences in income and race segregation, thus further consolidate our results. Everlasting debates between the two parties over coronavirus-related policies since Mar. 2020 can potentially explain the association. Survey-based results (Pickup, Stecula, and Van Der Linden 2020; Clinton et al. 2021; Center 2020) reveal that Democrats are more compliant with general mobility control and adoption of personal preventive measures such as mask-wearing, while Republicans appear more optimistic about the pandemic situation, and thus feel more comfortable in dining out, shopping and attending indoor events[9]. Such behavioral preferences are captured by Fig. 10, 11 in both the overall tendency of greater mobility reduction in Cluster-1 states and the differences in the relative magnitude of changes in each category with respect to the cluster's average mobility change. In Cluster 1, mobility drops in *Transportation*, *Finance*, *Professional*, *Public Admin* and *Hospitality* are substantially greater than that in Cluster 2. Since these categories cover various aspects of urban life from public service to business to personal consumption, the result indicates that partisan gaps span pervasively into all walks of life, acting as a strong power that regulates the social behavior of urban residents. Our observations corroborate with previous research findings that both COVID-19 policy stringency and citizen responses are substantially influenced by political inclination (Adolph et al. 2022; Clinton et al. 2021; Center 2020). While previous studies either use issued mandates or conduct surveys, our analysis from large-

[9]https://www.pewresearch.org/fact-tank/2021/03/24/despite-wide-partisan-gaps-in-views-of-many-aspects-of-the-pandemic-some-common-ground-exists/

scale online service data provides a finer-grained and more realistic picture. Moreover, our results provide evidence of people's differentiated actions beyond their differentiated attitudes toward restriction policies. Nevertheless, we note that our analysis method does not indicate causality or temporal order, thus readers should be cautious in interpreting our findings in a causal way.

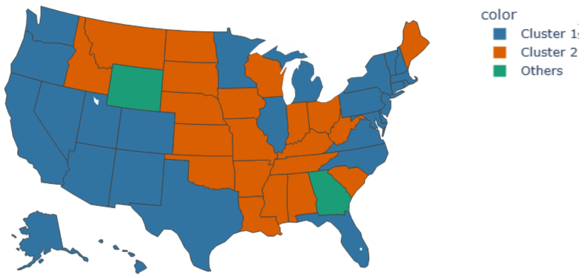


Figure 8: Geographical comparison between clustered mobility behavior change and state-level political inclination. Clustering results of mobility behavior change.

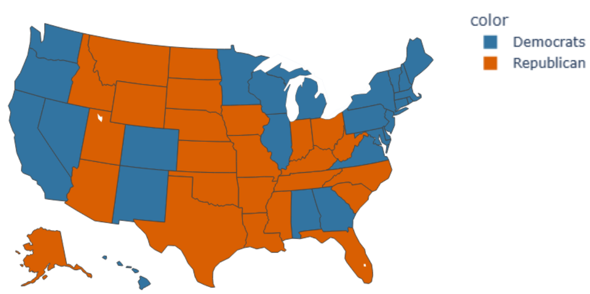


Figure 9: Geographical comparison between clustered mobility behavior change and state-level political inclination. Political inclination in 2020 presidential election.

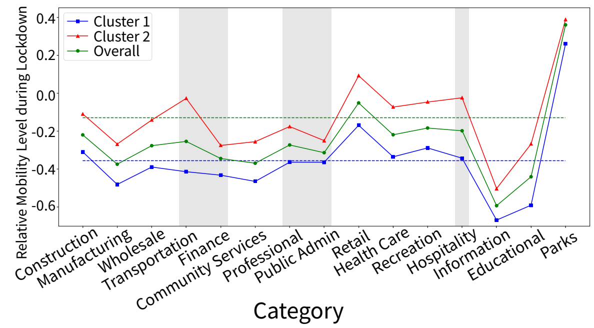


Figure 10: Comparison of mobility change of two dominating clusters by category. Relative mobility level during *lockdown* (w.r.t. *pre-pandemic*).

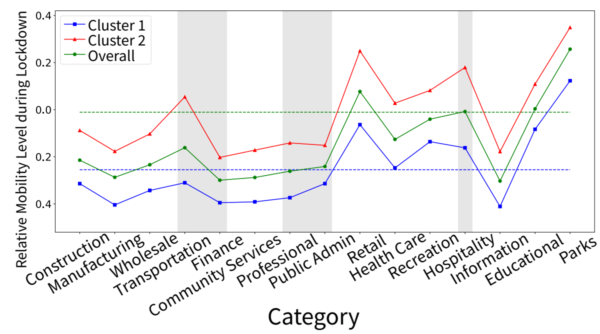


Figure 11: Comparison of mobility change of two dominating clusters by category. Relative mobility level during *reopening* (w.r.t. *pre-pandemic*).

Discussion

Our findings provide valuable insights for researchers, urban planners and business owners. **For researchers**, we provide a universal and easily extendable analytic framework of mobility behavior change, which can be adopted to study similar problems on different spatial or temporal scales. Our concrete findings drawn from passively-sensed large-scale data enhance previous studies with a comprehensive and realistic view, and deepen the understanding of urban mobility and its relationship with other important characteristics in urban life. Our analysis also evidences the value of online location service data in understanding real-world social phenomena, which entail much richer information about human-human relationships and human-location interaction that transcends traditional survey data. **For urban planners**, the five distinct patterns of visitation change we identify can be used as a reference when devising targeted policies to ease the burden of certain industrial sectors during epidemics. For example, big tech companies are usually more comfortable in shifting working modes to quickly adapt to the changing environment, but traditional industries or small businesses may suffer substantial pain in the transition, and thus the latter should receive more guidance in risk management and more support during hard times. The heterogeneity of recovery capability also highlights the importance of urban resilience, which can be improved preemptively by accelerating technical revolutions of traditional industries and maintaining a proper composition of different industrial sectors. **For business owners**, the mobility change patterns we find serve as a "teaser" about the business responses during crises and inform better preparations for future disturbance. For instance, it is important for business setups falling in vulnerable categories to improve their risk management and establish potential pathways to transform their business models (e.g., online order and delivery) if the current model is disrupted.

Our work has several limitations. First, the location service data used in this study have been aggregated to the monthly level, constraining our capability to analyze more granular temporal changes. If finer-grained data are available, we can naturally extend the current analysis to understand more subtle changes in mobility rhythms. Second, we classify urban venues at a relatively high level and may overlook certain intra-category differences. Nevertheless, our framework for estimating changes in urban mobility and experienced segregation can be readily applied to investigate into any specific type of urban venues. Third, our analysis mainly reveals correlations rather than causalities between features. As future work, we will explore causal analysis to get rid of the influences of confounders.

Conclusion

In this work, we utilize a large-scale location service dataset to systematically analyze the changes in urban venue visitation patterns in three phases of the COVID-19 pandemic. We conceptualize five patterns of mobility change, and rationalize the patterns with the nature of different venues and their function in the hierarchy of human needs. We analyze the change in experienced income and race segregation in different venues, and establish the link between mobility drop/recovery and change of experienced segregation. We discover two clusters of states with similar patterns of mobility change, and demonstrate the high resonance between their geographical distribution and the distribution of Democrat-leaning/Republican-leaning states. Our work provides an extendable framework for jointly analyzing urban mobility patterns across multiple time periods, and our findings contribute to better planning of urban resource distribution in the face of crises.

Ethics Statement

The mobility data from Safegraph are aggregated to the CBG level on a monthly basis, and thus do not contain any individual-level data. To further enhance privacy, differential privacy techniques (https://docs.safegraph.com/docs/monthly-patterns\#privacy) are applied, and groups with too few visitors are removed. The demographic data from American Community Survey are publicly available at https://www.census.gov/programs-surveys/acs/, which also reports data on the CBG level. Therefore, no approval from the Institutional Review Board was required by the authors' institutions.

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