Exploring store visit changes during the COVID-19 pandemic using mobile phone location data

Yunlei Liang[1], Kyle W. McNair[1], Song Gao[1], Aslıgül Göçmen[2,3]

1. GeoDS Lab, Department of Geography, University of Wisconsin-Madison, Madison, WI 53706, USA
2. Department of Geography, University of Wisconsin-Madison, Madison, WI 53706, USA
3. Nelson Institute for Environmental Studies, University of Wisconsin-Madison, Madison, WI 53706, USA
{yunlei.liang,kwmcnair,song.gao,gocmen}@wisc.edu

Abstract. When the World Health Organization (WHO) announced the pandemic of COVID-19, people around the globe scattered to stores for groceries, supplies, and other miscellaneous items in preparation for quarantine. The dynamics of retail visits changed dramatically due to the pandemic outbreak. The study intends to analyze how the store visit patterns have changed due to the lockdown policies during the COVID-19 pandemic. Using mobile phone location data, we build a time-aware Huff model to estimate and compare the visiting probability of different brands of stores over different time periods. We are able to identify certain retail and grocery stores that have more or fewer visits due to the pandemic outbreak, and we detect whether there are any trends in visiting certain retail establishments (e.g., department stores, grocery stores, fast-food restaurants, and cafes) and how the visiting patterns have adjusted with lockdowns. We also make comparisons among brands across three highly populated U.S. cities to identify potential regional variability. It has been found that people in large metropolitan areas with a well-developed transit system tend to show less sensitivity to long-distance visits. In addition, Target, which is a department store, is found to be more negatively affected by longer-distance trips than other grocery stores after the lockdown. The findings can be further applied to support policymaking related to public health, urban planning, transportation, and business in post-pandemic cities.

Keywords: location business intelligence, COVID-19, human mobility, foot traffic

1 Introduction

Day-to-day life has been dramatically changed by the novel coronavirus disease (COVID-19) pandemic. As of December 15th, 2020, there are over 70,000,000 confirmed cases of COVID-19 with over 1,600,000 deaths across the world (WHO, 2020). With many researchers are working on finding effective treatments to control this disease, many federal governments and institutions have provided a wide-ranging set of non-pharmaceutical interventions and policies to slow down the spread of COVID-19; some of these policies have aimed at reducing travel flows and close contacts between individuals (Aloi et al., 2020; Lai et al., 2020; Gao et al., 2020; Painter and Qiu, 2020).

In the United States, state and local governments have similarly enacted social distancing policies to limit contacts between individuals. These policies have included travel restrictions, closures of schools and nonessential businesses, bans on large social gatherings, restrictions for indoor dining at restaurants, and statewide mask and stay-at-home orders (Courtemanche et al., 2020; Hong et al., 2020). People have changed their movements and store visit behaviors in response to those measures (Chang et al., 2020; Gao et al., 2020; Huang et al., 2020; Pan et al., 2020).

Google published the COVID-19 Community Mobility Reports to help the public understand how individuals' movement, as measured by visits to workplaces and popular destinations including parks, restaurants, and grocery stores, have changed in response to the lockdown policies (Aktay et al., 2020). Based on those reports, a few studies analyzed the impact of lockdown on community mobility and identified different trends in visits to different places during pre-lockdown and after lockdown periods (Mohler et al., 2020; Saha et al., 2020; Chetty et al., 2020). From those studies, it has been found that the behavioral changes are not uniform across places as the reduction in mobility is different for different types of places (Chang et al., 2020) and also in different countries (McKenzie and Adams, 2020). Therefore, it is critical to further investigate the extent to which and how people's movements have changed. Some research studies have focused on discovering disparities in the movement patterns and related the change of mobility to different types of places people visit and different geographic areas or social groups people belong to. Li et al. (2020) used the origin-destination networks to understand how visits from Census Block Group to different types of urban hotspots have changed differently and how

In Shih-Lung Shaw and Daniel Sui (Eds): *Mapping COVID-19 in Space and Time: Understanding the Spatial and Temporal Dynamics of a Global Pandemic* (Chapter 13). pp. 253-275, Springer. DOI: 10.1007/978-3-030-72808-3_13

the reduction in movement vary across multiple U.S. cities. Another study by Hong et al. (2020) further combined localized socioeconomic, demographic and infrastructure information to discover whether the behavioral responses are related and affected by such characteristics. The researchers were able to identify distinct visit patterns in response to COVID-19 across neighborhoods and communities with different characteristics (Hong et al., 2020). In addition, Holtz et al. (2020) found that the mobility patterns of people in one area are greatly affected by the lockdown orders in its socially or geographically connected peer states. Those quantitative analyses provide insights into how lockdown policies affect mobility patterns from different perspectives. However, we still do not know much about how mobility patterns as measured by visits vary among particular stores and across different cities. Our work presented in this chapter explores this question about variability of mobility patterns among particular chain stores and across different cities in the U.S..

We use the definition of a brand as "a logo or branded store which has multiple locations all under the same logo or store banner" following the definition from our data provider (SafeGraph, 2020a). The store is a specific location of a certain brand; in our work, the "store" can be considered as a retail establishment. In this study, we use large-scale mobile phone location data to analyze customer visits to five popular chain-store brands in pre-lockdown and after lockdown periods across three large U.S. cities to examine any variation among the visits to different places. We employ a time-aware dynamic Huff (T-Huff) model to estimate the visit probability from a particular Census Block Group to a chain-store brand. The traditional Huff model is typically used to estimate the trade area of a certain store (Huff, 1963). A few studies have used the Huff model to delineate the trade area and calibrated it using data collected from user surveys or social media data (Suárez-Vega et al., 2015; Wang et al., 2016). For example, Wang et al. (2016) collected the social media posts to extract user samples and used that as the input to the Huff model for trade area delimitation. However, most of the Huff models are static, while the store visit patterns have temporal variations. The T-Huff model used in this study was proposed by Liang et al. (2020) in order to provide a second dimension of information (time) for trade area delineation besides the spatial dimension. By incorporating the temporal and spatial information in modeling people's visit patterns, the T-Huff model can capture the dynamics of visits and reflect the visit behaviors via the parameters of the model with higher accuracy than the traditional Huff model (Liang et al., 2020; McKenzie et al., 2015).

The contribution of this study is threefold: (1) We provide location business insights into the visit patterns by analyzing the median travel distance to each store and also by comparing the customer dwell time (the time spent in a store) distribution in different time periods. (2) We analyze the impacts of lockdown policies on store visits by comparing spatial distribution of visits using origin-destination mobility networks. (3) We are able to discover different visit patterns to different brands and identify regional variation in such visits using the T-Huff model.

The chapter is organized as follows. We first introduce the proposed T-Huff model in the methods section 2, which is followed by the data and study area in section 3. We then present comparative analyses, results and discussion in section 4. Finally, we conclude the study and share some thoughts for future work in section 5.

2 Methods

The original Huff model is primarily used to delineate the trade area of a store, which is an area containing potential customers (Huff, 1963). It can estimate the visiting probability from one customer to a particular store with the assumption that this visiting probability is related to the attractiveness of the visited store and the travel cost (such as distance or travel time) between the customer and the store. The attractiveness here can be considered as what the store can offer to its customers, usually this variable can be represented by the store size, or the number of goods in the store.

In this study, we employ the above-mentioned time-aware dynamic Huff model (T-Huff), which was proposed based on the fact that people's visit preferences also have temporal variations (Liang et al., 2020). The authors provided evidence that the T-Huff model has higher estimation accuracy than the original Huff model in their experiments across ten U.S. cities and it is able to model the store visit patterns from both spatial and temporal perspectives. In this study, we apply the T-Huff model to study the store visit dynamics during the COVID-19 pandemic. We briefly introduce the model formula below; more technical details can be found in the original paper.

$$P_{ijt} = \frac{\frac{S_j^{\alpha}}{D_{ij}^{\beta}}}{\sum_{j=1}^{n} \frac{S_j^{\alpha}}{D_{ij}^{\beta}}} * P_{jt} \tag{1}$$

$$P_{jt} = \frac{V_{jt}}{\sum_{t=1}^{m} V_{jt}} \tag{2}$$

where P_{ijt} represents the visiting probability from customer i to the store j within time window t, S_j is the attractiveness of the store j and D_{ij} is the distance between customer i and the store j, n is the number of stores that customer i would visit. Equation 1 shows that the visiting probability is a result of comparison: the probability of visiting store j is calculated by comparing across all the stores that customer i will visit. P_{jt} is the probability of visiting store j within time window t and V_{jt} represents the number of total visits to store j within time window t. In this study, the time window t is selected as one hour, which is the finest resolution regarding data availability. So for one week, there are 168-dimensional visiting probabilities for one customer to one store.

Before using this model to predict the customer visiting probability, we need to calibrate it by adjusting two parameters: attraction exponent (α) and distance-decay coefficient (β) to make sure the model can reflect the reality. For each brand in each city, we use the Particle Swarm Optimization (PSO) to find the optimal sets of parameters that fit the data the best. The PSO method was proposed based on the movement of a bird flock (Eberhart and Kennedy, 1995). It is selected for this study because it requires few assumptions and allows the design of different objective functions (Eberhart and Kennedy, 1995; Xiao et al., 2013; Liang et al., 2020). Given each set of α and β, we can calculate the estimated visiting probability using the T-Huff model. We also computed the visiting probability using the actual visits each store received based on the collected mobile phone location tracking data (in the following section 3) and considered it as the actual visiting probability. The cost function we used in the optimization function is the correlation between the estimated visiting probability and the actual visiting probability, and we try to maximize the correlation over the optimization process. For each brand in each city, we ran the optimization three times since there might be performance variations due to different starting positions. Based on the results from a few trials and the findings that PSO usually converges quickly (Shi and Eberhart, 1999), we decided to have 50 iterations for each time with each iteration containing 10 candidate sets of values. The sets of α and β values that have the highest correlation will be selected as the optimal parameter fitting result.

3 Data and Study Area

The Points of Interest (POIs) data for this study is provided by SafeGraph[1]. For each POI, the SafeGraph dataset contains its basic information including its location name, address, latitude/longitude, category, brand, etc. We selected four different types of POIs using the North American Industry Classification System (NAICS) code and conducted our analyses in three U.S. cities (New York, Los Angeles and Houston). For each category of POIs, we selected one or two top chain-store brands as the focused brand to study. The categories and specific brands are listed in Table 1. Those brands are selected because of two reasons: first, the five brands have the largest number of stores in their corresponding categories and are present in all three cities in our dataset; second, those brands are popular stores that are closely related to the daily life for many people living across the U.S. Analyzing the store visits to those brands may provide some representative and meaningful insights into human mobility pattern changes. Figure 1 shows the spatial distribution of the five chain-stores in our dataset in Los Angeles. McDonald's and Starbucks are present throughout the whole study area, whereas Target, Trader Joe's, and Whole Foods Market are primarily located in the northwestern Los Angeles according to the data provided by SafeGraph. Note that the POI database doesn't necessarily cover all the real-world stores for each brand.

In order to analyze the visit patterns in these brands, we use the "SafeGraph weekly patterns" dataset, which contains the place foot-traffic and aggregate information about how many visits are made to one POI, how often people visit each place, how long they stay, and where they come from[2]. For every POI, if a visit is accompanied by a mobile device, a trip from the home Census Block Group of the device owner to this POI is generated. The work of determining whether a device visits a POI is completed by

[1] `https://www.safegraph.com`
[2] `https://docs.safegraph.com/docs/weekly-patterns`

the data provider using the GPS data (SafeGraph, 2020b). The GPS points are first cleaned and then clustered if they are close in both space and time using a modified DBSCAN clustering algorithm. The clusters are then joined with a list of potential places which this cluster could have been referencing to. Then, a machine learning model called Learning-to-Rank is used to predict the most viable place using features such as distance between clusters and places, the type of the places and the dwell time of the visit. Based on this data, we are able to map the flows from customers' home Census Block Group to different stores. To discover the visit pattern changes under lockdowns during the COVID-19 pandemic, we selected two time periods for each city as the study time window. The first period is when COVID-19 started spreading and was declared a pandemic (March 11th, 2020). As the data is provided in a weekly format, we selected the two weeks March 2nd-8th and March 9th-15th to represent this period. For the second period, we focused on the weeks after statewide lockdown orders were issued. Our aim is to discover whether and how movement behaviors changed according to the lockdown orders. Based on the dates of the lockdown orders (New York, NY: March 22nd; Los Angeles, CA: March 19th; Houston, TX: April 2nd) (Wu et al., 2020), we picked the two weeks March 23rd-29th and March 30th-April 5th for New York and Los Angeles, and April 6th-12th and April 13th-19th for Houston as their post-lockdown periods, respectively.

Although the data used in this study come from a very large coverage — around 10% of mobile devices in the United States, it may still have sampling bias. The sampling bias has been examined in different geographic scales with three demographic factors: race, educational attainment and household income. The proportion of any given sub-group in the SafeGraph dataset should be the same as it in the US Census population if there's no sampling bias. The data provider has provided evidence that their panel data is generally well sampled showing high correlations with the true population and low sum of absolute bias (Squire, 2020), although a small number of the Census Block Groups show some extreme outliers and this may be related to the process of linking a device to a specific Census Block Group.

This research got an IRB waiver from the University of Wisconsin-Madison for using aggregated mobile phone data.

Table 1: The chain-store brands and their categories

Brand	Category	NAICS code
Starbucks	Snack and Nonalcoholic Beverage Bars	722515
McDonald's	Limited-Service Restaurants	722513
Target	Department Stores	452210
Whole Foods Market	Grocery Stores	445110
Trader Joe's	Grocery Stores	445110

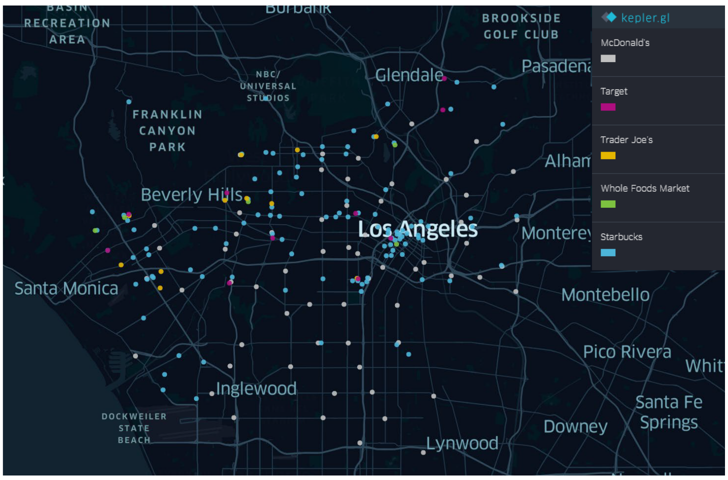


Fig. 1: The locations of five brands (McDonald's, Target, Trader Joe's, Whole Foods, and Starbucks) of stores in Los Angeles (in our database provided by SafeGraph).

4 Results and Discussion

4.1 Store Foot-traffic and Dwell Time Distribution Changes

We first analyzed the specific foot-traffic change to each chain-store brand and discovered how the store visits have been impacted by the lockdown orders during the COVID-19 pandemic.

Table 2, 3, 4 show the foot-traffic statistics including the number of stores, the number of total visits, the average visits, and the reduced percentage of average visits over the two periods for the three cities, respectively. We find that the number of stores of the same brand (with active visits) varies across three cities but the differences are generally not very large. The biggest difference is for Starbucks, New York City has almost twice the number of Starbucks compared to the other two cities. By comparing the average store visits over the two time periods, it shows that all stores in each city have much fewer average visits in the periods after the lockdown order was announced. Most of the stores lost more than 50% of their visits in the later period. Different cities show different trends in which stores have the greatest decrease in these two time periods. New York City had the largest decrease percentage of visits in all brands. This can be related to the fact that New York had the most COVID-19 cases in April and many people stayed at home to avoid the infection (The New York Times, 2020). It is also possible that people in New York City did not drive as much and therefore did not use drive-thru opportunities in McDonald's and Starbucks.

In addition to the store visits, in each brand, we also analyzed the total count of visitors based on the bucketed dwell times. The bucketed dwell times represent five intervals for store visits: less than 5 minutes, 5 to 20 minutes, 21 to 60 minutes, 61 to 240 minutes, and greater than 240 minutes. Figures 2, 3 and 4 show a histogram of total visitor counts by each brand in the three cities over the two time periods.

Table 2: Store visit statistics in Los Angeles

	early two weeks			later two weeks			
	stores	visits	mean visits	stores	visits	mean visits	% of reduced visits
McDonald's	63	16358	259.7	63	8779	139.4	46.3
Starbucks	113	17866	158.1	105	7790	74.2	53.1
Target	10	6183	618.3	10	3459	345.9	44.1
Trader Joe's	11	2562	232.9	11	999	90.8	61.0
Whole Foods Market	5	615	123.0	5	274	54.8	55.4

Table 3: Store visit statistics in New York

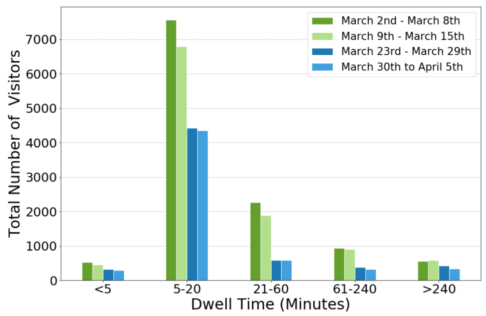
	early two weeks			later two weeks			% of reduced visits
	stores	visits	mean visits	stores	visits	mean visits	
McDonald's	55	13188	239.8	53	2875	54.3	77.4
Starbucks	216	47703	220.9	212	8134	38.4	82.6
Target	8	4453	556.6	7	1400	200.0	64.1
Trader Joe's	7	591	84.4	6	152	25.3	70.0
Whole Foods Market	9	1432	159.1	8	502	62.8	60.6

Table 4: Store visit statistics in Houston

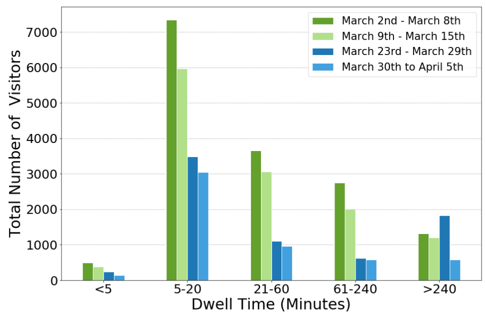
	early two weeks			later two weeks			% of reduced visits
	stores	visits	mean visits	stores	visits	mean visits	
McDonald's	109	41172	377.7	107	22227	207.7	45.0
Starbucks	114	43447	381.1	106	17643	166.4	56.3
Target	15	18374	1224.9	15	10622	708.1	42.2
Trader Joe's	3	1162	387.3	3	619	206.3	46.7
Whole Foods Market	9	2022	224.7	8	1023	127.9	43.1

The left side of Figure 2 shows the dwell time patterns for McDonald's store visits. In all three cities prior to the lockdowns, the highest frequency of visits were between 5-20 minutes. Similarly, in all three cities after the lockdown, the highest frequency of visits were still between 5-20 minutes. However, a difference emerged between cities: the number of visitors in Houston and Los Angeles McDonald's stores were higher than visitors to New York McDonald's. Comparing the changes over the two weeks in three cities, New York City shows the greatest drops in all time intervals, corresponding to what we discovered from our analysis on the number of store visits.

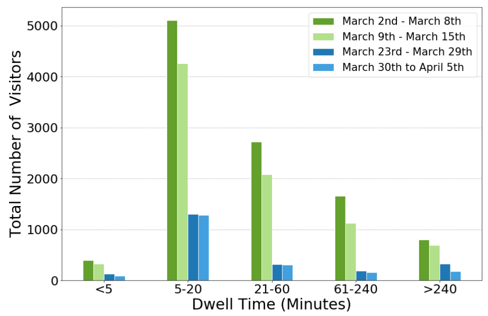
Starbucks, a snack and non-alcoholic beverage bar category brand, shows a high volume of visitors in the 5-20 minute dwell time interval in the right side of Figure 2. Compared with McDonald's, more people spent longer time (more than 20 minutes) in Starbucks in the early two weeks. Though the early period indicates a higher count of visitors, we see a tremendous decrease during the latter two weeks. Similarly as we mentioned before, New York City shows the largest difference in visitors in the two time periods.



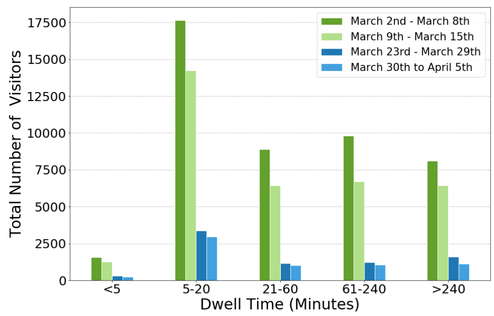
(a) Los Angeles - McDonald's



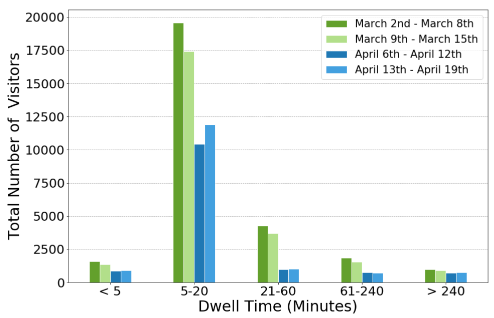
(b) Los Angeles - Starbucks



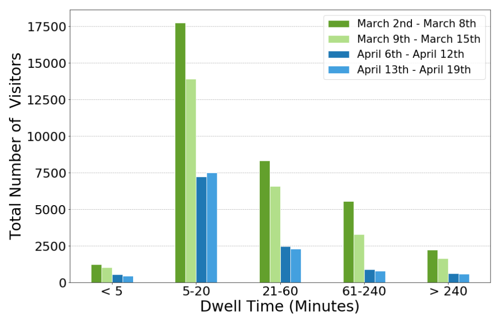
(c) New York - McDonald's



(d) New York - Starbucks



(e) Houston - McDonald's

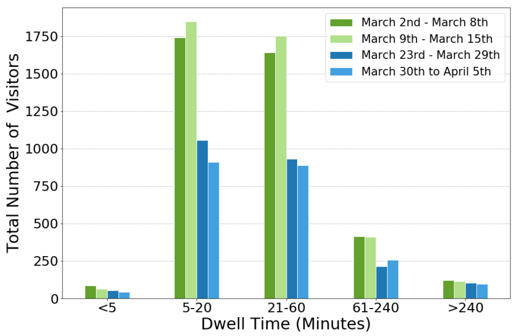


(f) Houston - Starbucks

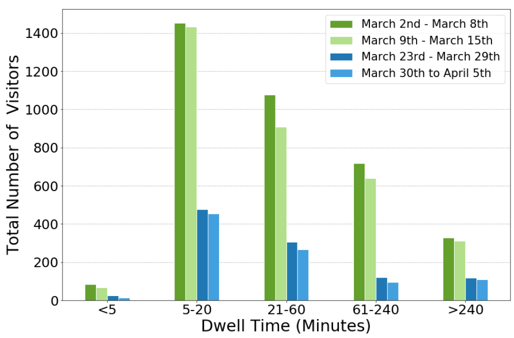
Fig. 2: The dwell time distribution for McDonald's and Starbucks.

The dwell time distribution for Target, a department store, is shown in Figure 3. In Los Angeles and Houston, the number of visits in the 5-20 minute and 21-60 minute intervals was very high and visits longer than 60 minutes were much lower. These two cities show a similar trend in the later two-week periods. Although New York City Target stores had a high number of visitors for the 5-20 minutes and 21-60 minutes intervals, they also had a high number of visits that took place over 60 minutes in the early two weeks. During the later period, New York City Target stores had noticeably much lower visitor counts for all time intervals. Public was concerned about the sufficient supply of goods, therefore, they may have spent extra time shopping for additional items and storing them in the early period. In general, the number of Target store visits was decreased for all time periods in the lockdown periods for all three cities, likely reflecting the preparedness with storage of home goods in the earlier period and the fast-pace of shopping consumers have adopted during the pandemic to limit their exposure to different parts of stores and different customers.

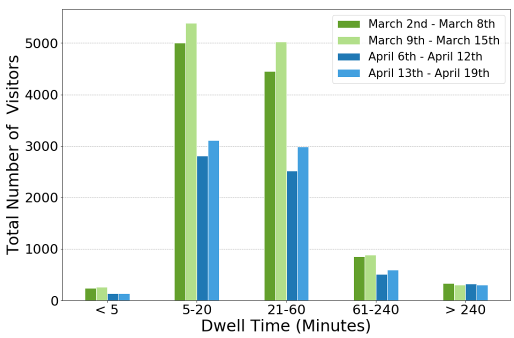
Finally, as shown in Figure 4, we have a comparison of the grocery store brands Whole Foods Market and Trader Joe's. One finding is that in all three cities, there were more visits in the March 9th - March 15th week than the earlier week in the 21-60 minutes dwell time. This is also the week that COVID-19 was declared by WHO as a global pandemic (World Health Organization, 2020). Therefore, the pandemic announcement, more specifically the willingness to stock up on groceries during a pandemic and longer lines may be an indicator to why people spent more time in grocery stores to purchase food among others.



(a) Los Angeles

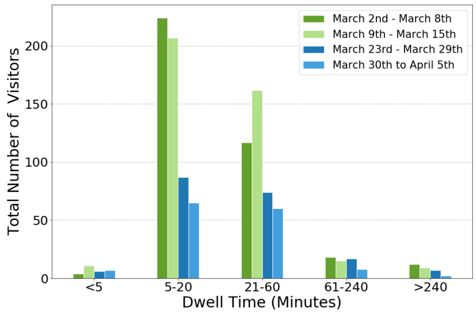


(b) New York

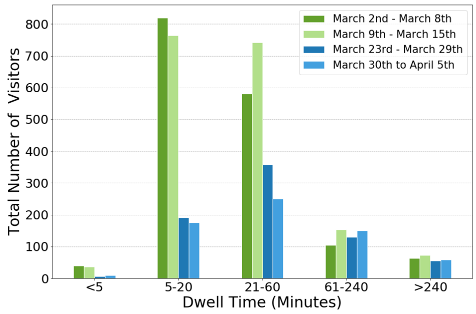


(c) Houston

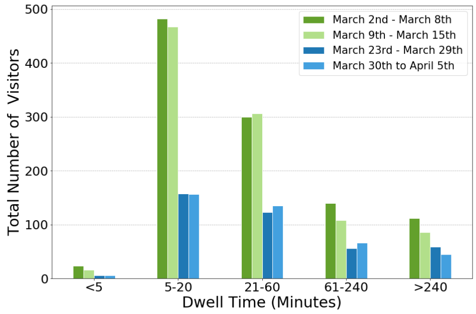
Fig. 3: The dwell time distribution for Target.



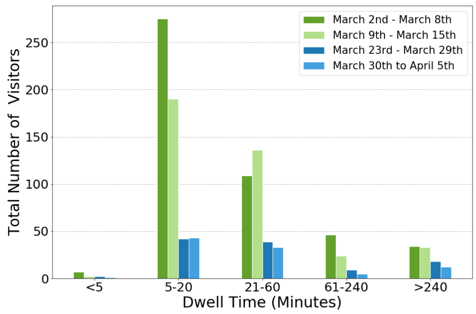
(a) Los Angeles - Whole Foods Market



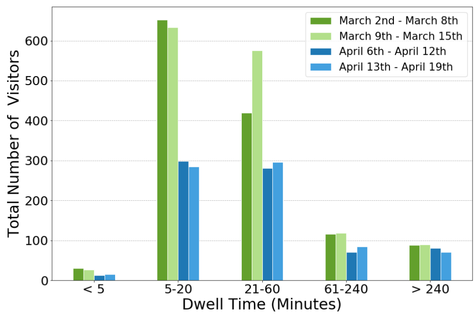
(b) Los Angeles - Trader Joe's



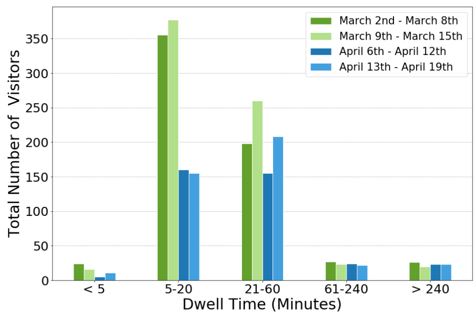
(c) New York - Whole Foods Market



(d) New York - Trader Joe's



(e) Houston - Whole Foods Market



(f) Houston - Trader Joe's

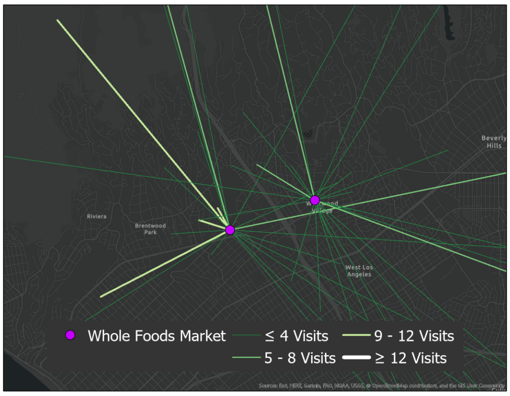
Fig. 4: The dwell time distribution for Grocery Store Brands.

4.2 Spatial Flow Distribution and Distance Decay

Using the collected mobile phone location data, we generated the origin-to-destination (OD) flow maps from the visitor's home Census Block Groups to each store location and compared the visit variations from the spatial point of view. Figure 5 displays maps for each of the three cities in this study showing visitor frequencies from home Census Block Groups to Whole Food Market stores in the two time periods. During the early two-week period, the flow maps reveal high frequency in various distances between Whole Foods Market store location and the visitor's home Census Block Group. There are also a few trips with frequency higher than 12 times in the early period. Most of the high-frequency trips (lighter colors) are within relatively close proximity to the store and there are also many long-distance visits with low frequency (darker colors) on the map.

For the latter two weeks, the maps reveal there is a lower frequency in visits. This is indicated by the overall colors on the map appear darker because some high-frequency visits represented by the light colors disappeared. This could be an outcome of stocking up on groceries as well as limiting visits to stores, especially if an individual used public transportation. For instance, during the lockdown orders, cities across the country have advised the public to avoid using public transportation as much as possible (Tirachini and Cats, 2020). For Houston, however, some long-distance trips have lighter colors in the later period (e.g., the two lines in the southeastern corner in Figure 5(f)), meaning that some people still travelled long distances to visit Whole Foods Market more often than in the earlier two weeks. This could be due to Whole Foods Market having specialty products that cannot be found in other grocery stores. For those remaining visits, visitors' home Census Block Groups were generally closer to Whole Foods Market compared with the early period. So with the lockdown orders, in addition to the reduction in the number of visits to Whole Foods Market stores, there is also a reduction in long-distance trips to visit such stores based on the flow maps. Similar findings have also been identified by other human mobility change research in the U.S. during the COVID-19 pandemic, providing evidence that the lockdown policies have made the short-distance trips gain a higher weight out of total trips than before (Gao et al., 2020; Aloi et al., 2020; The National Academies of Sciences, Engineering, and Medicine, 2020).

(a) Los Angeles - Early 2 Weeks



(b) Los Angeles - Later 2 Weeks

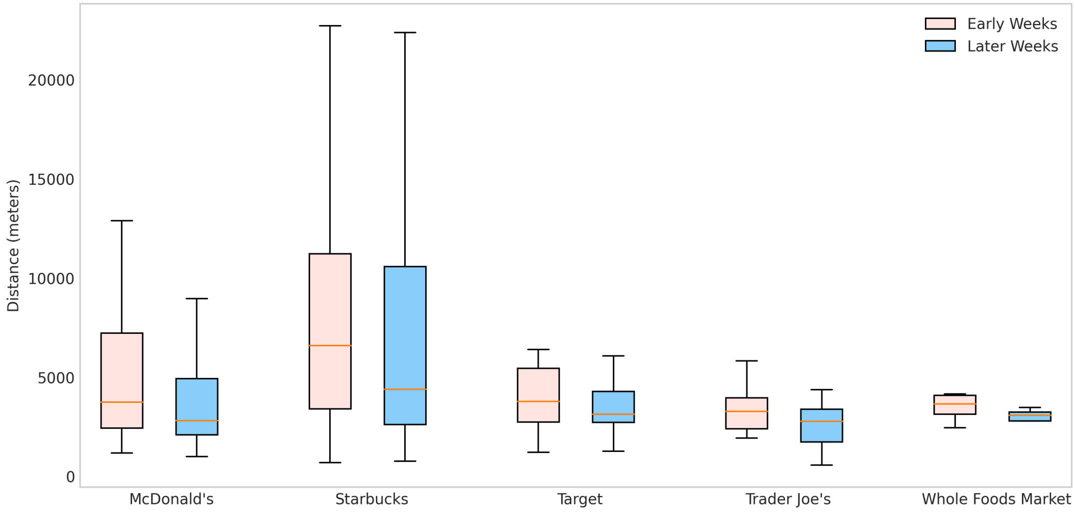
(c) New York City - Early 2 Weeks

(d) New York City - Later 2 Weeks

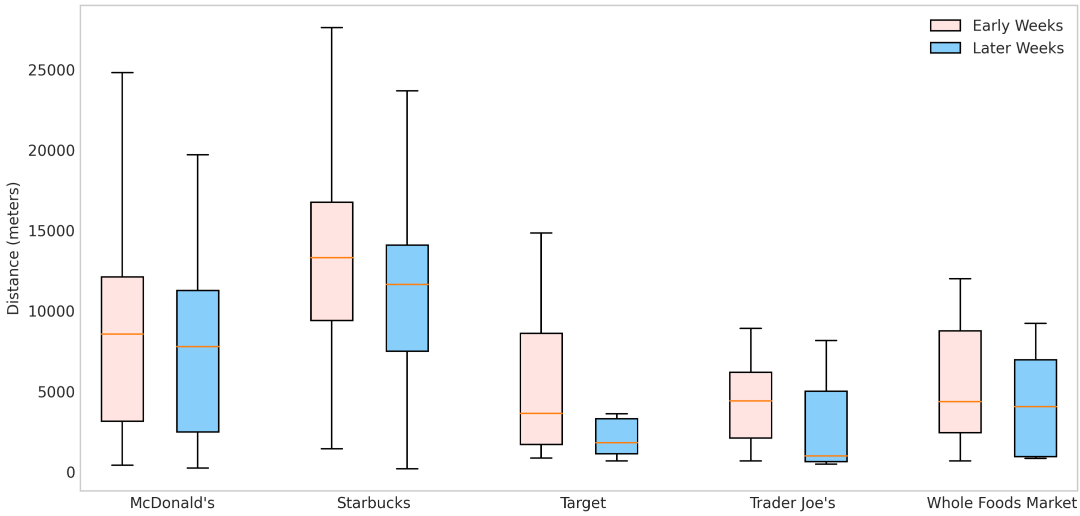
(e) Houston - Early 2 Weeks

(f) Houston - Later 2 Weeks

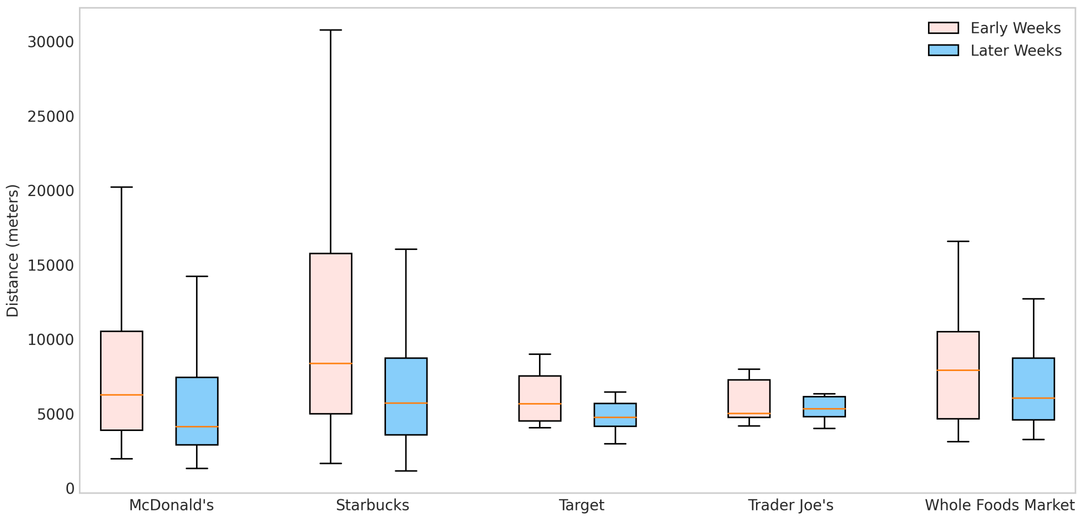
Fig. 5: Frequency of Visits from home Census Block Groups to Whole Foods Markets.



(a) Los Angeles



(b) New York



(c) Houston

Fig. 6: The median travel distance (in meters) distributions for stores in Los Angeles, New York and Houston (outliers removed).

Besides the flow maps, for each store of each brand, we computed the median travel distance from all the visitors to that store each week. Figure 6 shows the box plots of the median distance distribution for all the stores of each brand in the three cities. The red boxes are results for the early two weeks while the blue boxes are for the later weeks. In each boxplot, the interquartile ranges (IQR) of the data (from Q1: 25 percentile to Q3: 75 percentile) is represented in a box with an orange line at the median (Hunter et al., 2020). The two whiskers show the upper and lower range of the data, the upper whisker is defined as $Q3 + 1.5 * IQR$ and the lower whisker equals to $Q1 - 1.5 * IQR$. All data points beyond the whiskers are treated as outliers and excluded from our analysis.

For Los Angeles (Figure 6a), in general, both the range between whiskers and the IQR of McDonald's, Target and Trader Joe's have a trend of moving down in the two time periods we examined, meaning that most of the travel distances became shorter in the latter lockdown period. Starbucks does not have a very obvious range change between the two time periods but it has a smaller median value in the later period, indicating that most trips to Starbucks have become shorter. Whole Foods Market actually shows a higher value for the bottom whisker in the later period, meaning that it has fewer short-distance trips. This result might be affected by the limited trip data for Whole Foods Market stores, as shown in Table 2, we only have 5 Whole Foods Market stores in Los Angeles in our dataset and fewer trips during lockdowns. So the change of travel distance to one store can easily affect the overall distribution of data.

For New York (Figure 6b), all brands show a trend of moving down to smaller data ranges in the later weeks. Target has the most significant change: the range between two whiskers as well as the range of interquartile both shrank greatly in the later weeks. For Trader Joe's, its median travel distance dropped sharply, showing that though the range of the distance only changed slightly, the shorter-distance visits to this brand have a higher weight in the later weeks compared with that in the early period.

For Houston, most of the brands in Figure 6c show the trend of having shorter travel distances as well as smaller data ranges in the later weeks compared with the early weeks. McDonald's and Starbucks both have fewer long travel distances as the upper whisker become much smaller in the later period. One noticeable difference is for Trader Joe's: it actually has a larger median value in the later weeks based on our data, which is the opposite of all other brands.

Given that the observed visit data are about 10% representative samples of the mobile devices in the U.S.[3], we further built the T-Huff model for each brand in each city during each time period to understand the overall spatial interaction patterns, which are important for location business insights as we cannot track all the customers across all the neighborhoods in different cities. A set of optimal α, β parameter values for the T-Huff model are obtained through the optimization. Table 5 shows the optimization results using the correlation between observed visit probability and fitted probability for Los Angeles. In general, the optimal correlations we obtained are very high and most of them are higher than 0.99, meaning that the predicted visiting probability is strongly related to the actual probability.

Comparing the results for each brand specifically, the parameter α controls the weight of store attractiveness in the model and the parameter β controls the impact of distance. A larger β means that distance plays a more important role when people take this trip. As the distance is the denominator in the visiting probability calculation (Equation 1), a higher β indicates that people are less likely to visit a store that is far away from their home location (Liu et al., 2014; Liang et al., 2020). Therefore, when we compare the β values across brands, we may be able to discover people's visit preferences for long-distance trips to different brands in different time periods.

When we look row by row and compare the two β values for each brand in Table 5, Starbucks, Target and Trader Joe's has increased β values in the latter two weeks, meaning that Los Angeles residents seemed to become less willing to travel longer distances to visit those three brands after the lockdown. For McDonald's and Whole Food Market, we have lower β values in the later weeks. When we look back at Figure 6a, for Whole Foods Market it indeed has a higher value for its lower whisker in the later periods, showing that we lost short travel distances for this brand. This makes the data have more longer-distance trips in the latter period and might lead to the decreased β value from the optimization result.

[3] https://www.safegraph.com/blog/what-about-bias-in-the-safegraph-dataset

Table 5: Optimization using correlation for Log Angeles

location name	early two weeks			later two weeks		
	alpha	beta	correlation	alpha	beta	correlation
McDonald's	0.0087	0.1746	0.9969	0.0304	0.0984	0.9939
Starbucks	0.0040	0.0375	0.9958	0.0001	0.0810	0.9958
Target	0.0053	0.0913	0.9955	0.0310	0.1110	0.9922
Trader Joe's	0.0110	0.0651	0.9992	0.0866	0.1017	0.9932
Whole Foods Market	0.0120	0.1277	0.9933	0.0007	0.0937	0.9302

Table 6 shows the optimization results for New York. By comparing two β values, we see that McDonald's, Target and Whole Foods Market have increased β values, meaning that distance has a greater negative impact when people visited those brands. Starbucks and Trader Joe's have decreased β values in the latter two weeks. In Figure 6b, Starbucks and Trader Joe's are the two brands with the slightest data range changes over the two periods. The visit pattern to those two brands in New York over the study periods may not have changed very significantly.

Table 6: Optimization using correlation for New York

location name	early two weeks			later two weeks		
	alpha	beta	correlation	alpha	beta	correlation
McDonald's	0.0153	0.084	0.9968	0.036	0.092	0.9877
Starbucks	0.0029	0.1336	0.9962	0.0259	0.0797	0.9929
Target	0.0331	0.0898	0.9963	0.0036	0.0976	0.9947
Trader Joe's	0.001	0.0685	0.997	0.1051	0.0177	0.9944
Whole Foods Market	0.0209	0.0549	0.9948	0.0239	0.0803	0.996

Table 7 provides the optimization results for Houston. McDonald's and Target both have higher β values for the latter weeks, showing that distance become more important to consider when visiting a store after the lockdown. For all other three brands, their β values dropped dramatically to less than 0.1 in the latter weeks. One reason for this might be the later period has fewer data and the optimization did not perform well when the data size is very small. In addition, as Los Angeles and New York had much more positive cases for COVID-19 over our study periods compared with Houston, it is also possible that people in Houston did not have consistent visit changes in response to COVID-19 in comparison with people in Los Angeles and New York; therefore, the results did not reveal a clear long-distance movement reduction for Houston.

Table 7: Optimization using correlation for Houston

location name	early two weeks			later two weeks		
	alpha	beta	correlation	alpha	beta	correlation
McDonald's	0.0053	0.0103	0.9978	0.0077	0.0503	0.9985
Starbucks	0.0066	0.1891	0.997	0.0088	0.0678	0.9958
Target	0.0025	0.2929	0.9975	0.0147	0.3333	0.9975
Trader Joe's	0.0008	0.2855	0.9987	0.0274	0.0351	0.9916
Whole Foods Market	0.0047	0.3047	0.9988	0.0052	0.0036	0.9931

4.3 Discussion

After we combined the results for all three cities, we found that Target, which is defined as a department store, has increased β values in the latter two weeks for all cities. This consistent result indicates that people are less likely to travel long distances to visit this brand during the lockdown period. This may correspond to the lockdown orders that were issued to limit people's travels only to essential businesses. It is understandable that consumers would limit their purchases during a pandemic to essential items such as food and daily household goods such as cleaning supplies and toilet paper. Target brand carries household goods as well as groceries in some of its stores, and much more including clothing and travel-related items. Because much of those essential items (i.e., food and daily household goods) can be found in nearby other grocery stores, the need for individuals to travel long distances to Target may have been decreased. Moreover, many individuals go to Target occasionally and do not shop there on a daily or weekly basis. So it is possible that individuals may have shopped in greater quantity when the pandemic started in the early period not necessitating trips in the short-run. In this case, people may still visit nearby grocery stores as before, but they might show less interest in visiting department stores such as Target. Here, we use mobile phone location big data to show some evidence of this hypothesis.

McDonald's and Starbucks do not have a consistent trend of the β value changes over time, likely because there are usually more of these two brands in communities compared with the department stores and grocery stores. They do not require large spaces like department stores or large grocery stores and are designed to be located near people for easy access and convenience. So the visits to them may be less affected by distance as the visits are in relatively close proximity.

When we compared the overall β values across three cities, New York City has the lowest β value on average. If we only compare the β values for Target, Trader Joe's and Whole Foods Market (which are stores easier to be affected by distance than McDonald's and Starbucks) in the two periods, out of the six β values New York City has the lowest β value for four times. A lower β indicates that distance has a weaker negative impact on the travel behavior and people are less likely prevented to visit stores by the long distance between them and the stores (Liang et al., 2020; Liu et al., 2014).

New York has a much different urban make up than many other large cities in the U.S., including Los Angeles and Houston. New York City is considered the most automobile-independent large city due to its residential density, its urban fabric with mixed-use development, and its well-developed public transit system (Rundle et al., 2007; Newman and Kenworthy, 2015). Similarly, New York is considered the most compact and connected metropolitan area in the U.S. based on a rating of 221 metropolitan areas for urban sprawl (Smart Growth America, 2014). The Houston metropolitan area, on the other hand, appears as 182nd in this index; in other words, it is among the most sprawling and automobile-dependent metropolitan areas in this rating. Earlier studies have identified the sensitivity to travel distance also varies in different cities based on different transportation mode the city has (Pun-Cheng, 2016; Liang et al., 2020). Though the general consensus is that the cost of a trip is proportional to the distance, it may not be the case when people are taking public transportation, where the cost can be similar for different lengths of trips (Pun-Cheng, 2016). Therefore, residents in New York City may be more willing to travel a little further than the other two cities due to its mature public transportation system. This might be one of the reasons why New York City always has lower distance-decay coefficient (β) values.

However, due to health concerns and the lockdown policy, people may have limited access to public transportation. One study in Spain found that public transport users have a greater decrease compared with private car users after the confinement measures imposed (Wang et al., 2020; Aloi et al., 2020). For New York City, the traffic was estimated to decrease by about 35% compared with the same period in 2019 (Aloi et al., 2020). However, based on the β values we found, people in New York City are still more likely to travel a longer distance to visit the same store than the other two cities, meaning that people's visit preferences or those essential workers at stores may remain the same despite the effects of the pandemic.

In addition to the T-Huff model, we also conducted a multiple linear regression (MLR) analysis to discover how the neighborhood characteristics and the POI attraction are associated with the visit changes under the lockdown policies during the COVID-19 pandemic. By including multiple demographic variables from US Census to predict the visit changes to McDonald's in Los Angeles, we found that population, median age and the ratio of people having a bachelor's degree or higher have a positive contribution to the drop in the visit. In other words, in areas with a higher population, higher median age and higher education level (larger ratio of people with a bachelor degree or higher), people tend to show a larger drop in the visit in the post-lockdown period. Similar findings have also been discovered by some studies showing that the education and income level may affect people's response to the lockdown policies (Brzezinski et al., 2020). Such analyses may help further understand the impacts of the lockdown policies in different communities and help adjust the policies to encourage less responsive neighborhoods to better follow the policies. A segregation effect was also found by Bonaccorsi et al. (2020) that the mobility contraction is stronger in areas where inequality is higher. A more comprehensive understanding of how individuals have been impacted, why they responded differently and who are the most fragile individuals under the lockdowns requires further research.

5 Conclusion and Future Work

In this study, we employed mobile phone location data to examine visit changes to different types of chain stores in two time periods (the period when COVID-19 became a pandemic and started spreading in U.S. and the period after a lockdown order was announced). We are able to discover the significant visit changes to five major chain-store brands in response to COVID-19 in three large U.S. cities (Los Angeles, New York and Houston). By applying a time-aware Huff model, we further examined different visit pattern changes to different types of stores. People in general reduced longer distance trips and became less willing to travel longer to some stores such as Whole Foods or Trader Joe's in different cities. Target, which is a department stores, is found to always have increased distance-decay coefficient (β) values in the latter two weeks using the T-Huff model, meaning that longer distance trips had a greater negative impact when visiting this brand for customers after lockdown based on our study.

One limitation of this study is that the locations of the brands in our study may affect the accessibility to them by different transport modes. Some stores may not be easily accessed by public transit and this can affect people's willingness to visit those stores. Future work can further examine the distance from the stores to public transit routes and stops, and include this feature in the store attractiveness estimation as a factor related to the visit probability.

Some future research directions can be explored by expanding the scope of this study. For example, in addition to understanding the visits to specific brands, it is also possible to consider each business category as a whole and compare the visit patterns to different types of POIs such as restaurants or grocery stores. This may help provide a broader picture of the movement behaviors as many brands are local and cannot be compared across multiple cities. It is also worth studying how individuals' movements have changed with time. We only picked two time periods, one being at the beginning of the pandemic and the other soon after lockdowns were announced. However, it would be critical to investigate how mobility was adjusted under different policies as the states started reopening. Including longer investigation periods could help examine the influence of different policies as well as "behavioral fatigue", the phenomenon that people have become tired of staying at home and less self-regulating in the later periods of the pandemic (Sibony, 2020; Brodeur et al., 2020; Zhang et al., 2020).

The results of this study may also provide suggestions for policy making related to public health. For example, the predicted temporal visit probabilities to different stores can be used to advise customers on finding a suitable time for shopping to avoid the crowds during the peak visit hours. Similarly, the temporal feature can also be applied to help businesses plan for reopening. For example, it can provide temporal information to stores that are considering opening part-time to select the most appropriate hours for reopening. In addition, analyzing how the store visit pattern has changed can help understand the effectiveness of the lockdown policies and provide insights for decision-making when governments are considering adjusting lockdown orders and preparing for reopening. Businesses in conjunction with local and state authorities could use findings from ours and other similar studies to advise store visit hours, with the assumption that there will be a long way to COVID-19 recovery even with the good news of vaccines and there might be similar outbreaks in future and that we might need to limit contact among individuals.

Beyond lockdowns, COVID-19 has also triggered different business and urban planning practices that have targeted safe business experiences for the health of individuals and the economy. These practices aim to reduce human interaction, especially in closed spaces. Many businesses have transferred their activities from indoors to outdoors: some restaurants began to provide outdoor dining options and some retail stores provided their wares on city sidewalks (Hendrickson, 2020). While these practices are not new in many parts of the world, they are new in most U.S. cities as such business practices are typically not allowed in cities due to existing zoning regulations. Post-COVID urban planning practice in the U.S. will likely see an increase in the relaxation of these codes and regulations. Moreover, the demand for places that individuals can be active outside as well as to experience the urban environment has risen significantly; prompting the expansion of sidewalks and conversion of streets to pedestrian-only streets across the globe (Wojahn, 2020). Scholars, planners, and visionaries have been contemplating on what the post-pandemic city will look like and whether COVID-19 will be detrimental to the city itself (Couclelis, 2020). We are optimistic, just like Couclelis is, that the city will survive, as it has done so in the past in the face of adversity as well as technological innovation, since the various cultural, economic, education, and social opportunities and the experiences of the built and natural environments cities offer are among the most important aspects of urban living. The planning practice and resulting outcomes will likely differ significantly from the practices and outcomes of the past several decades; indeed we imagine that post-pandemic cities may make our urban environments less automobile-dependent with the integration of land uses so that individuals can access services and goods more easily as well as with additional outdoor experience opportunities with increased greenery, active transportation options (e.g., bike lanes and paths), and dedication of outdoor space for public and businesses. Ultimately, these are strategies that sustainability-minded planners have been trying to bring to communities for several decades, and a pandemic might simply force us to do that.

Acknowledgments

The authors would like to thank the funding support provided by the National Science Foundation (Award No. BCS-2027375). Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation. Support for this research was provided by the University of Wisconsin - Madison Office of the Vice Chancellor for Research and Graduate Education with funding from the Wisconsin Alumni Research Foundation. This research was also supported by SafeGraph and The We Company (WeWork) through academic collaboration with the Geospatial Data Science (GeoDS) Lab at the University of Wisconsin - Madison.

Bibliography

A. Aktay, S. Bavadekar, G. Cossoul, J. Davis, D. Desfontaines, A. Fabrikant, E. Gabrilovich, K. Gadepalli, B. Gipson, M. Guevara, et al. Google COVID-19 community mobility reports: Anonymization process description (version 1.0). *arXiv preprint arXiv:2004.04145*, 2020.

A. Aloi, B. Alonso, J. Benavente, R. Cordera, E. Echániz, F. González, C. Ladisa, R. Lezama-Romanelli, Á. López-Parra, V. Mazzei, et al. Effects of the COVID-19 Lockdown on Urban Mobility: Empirical Evidence from the City of Santander (Spain). *Sustainability*, 12(9):3870, 2020.

G. Bonaccorsi, F. Pierri, M. Cinelli, A. Flori, A. Galeazzi, F. Porcelli, A. L. Schmidt, C. M. Valensise, A. Scala, W. Quattrociocchi, et al. Economic and social consequences of human mobility restrictions under COVID-19. *Proceedings of the National Academy of Sciences*, 117(27):15530–15535, 2020.

A. Brodeur, A. Clark, S. Fleche, and N. Powdthavee. COVID-19, lockdowns and well-being: Evidence from Google trends. 2020.

A. Brzezinski, G. Deiana, V. Kecht, and D. Van Dijcke. The COVID-19 pandemic: government vs. community action across the united states. *Covid Economics: Vetted and Real-Time Papers*, 7:115–156, 2020.

S. Chang, E. Pierson, P. W. Koh, J. Gerardin, B. Redbird, D. Grusky, and J. Leskovec. Mobility network models of covid-19 explain inequities and inform reopening. *Nature*, pages 1–8, 2020.

R. Chetty, J. N. Friedman, N. Hendren, and M. Stepner. Real-time economics: A new platform to track the impacts of COVID-19 on people, businesses, and communities using private sector data. *NBER Working Paper*, 27431, 2020.

H. Couclelis. There will be no post-COVID city. *Environment and Planning B: Urban Analytics and City Science*, 47(7):1121–1123, 2020.

C. Courtemanche, J. Garuccio, A. Le, J. Pinkston, and A. Yelowitz. Strong Social Distancing Measures In The United States Reduced The COVID-19 Growth Rate: Study evaluates the impact of social distancing measures on the growth rate of confirmed COVID-19 cases across the United States. *Health Affairs*, pages 10–1377, 2020.

R. Eberhart and J. Kennedy. A new optimizer using particle swarm theory. In *MHS'95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science*, pages 39–43. IEEE, 1995.

S. Gao, J. Rao, Y. Kang, Y. Liang, J. Kruse, D. Dopfer, A. K. Sethi, J. F. M. Reyes, B. S. Yandell, and J. A. Patz. Association of mobile phone location data indications of travel and stay-at-home mandates with COVID-19 infection rates in the US. *JAMA Network Open*, 3(9):e2020485–e2020485, 2020.

V. Hendrickson. Shopping al fresco: New York City will allow stores to operate outside., 2020. https://www.marketwatch.com/story/shopping-al-fresco-new-york-city-will-allow-stores-to-operate-outside-11603923938.

D. Holtz, M. Zhao, S. G. Benzell, C. Y. Cao, M. A. Rahimian, J. Yang, J. N. L. Allen, A. Collis, A. V. Moehring, T. Sowrirajan, et al. Interdependence and the cost of uncoordinated responses to COVID-19. 2020.

B. Hong, B. Bonczak, A. Gupta, L. Thorpe, and C. E. Kontokosta. Exposure density and neighborhood disparities in COVID-19 infection risk: Using large-scale geolocation data to understand burdens on vulnerable communities. *arXiv preprint arXiv:2008.01650*, 2020.

X. Huang, Z. Li, Y. Jiang, X. Li, and D. Porter. Twitter reveals human mobility dynamics during the covid-19 pandemic. *PloS one*, 15(11):e0241957, 2020.

D. L. Huff. A probabilistic analysis of shopping center trade areas. *Land economics*, 39(1):81–90, 1963.

J. Hunter, D. Dale, E. Firing, M. Droettboom, and the Matplotlib development team. matplotlib.pyplot.boxplot, 2020. `https://matplotlib.org/3.1.1/api/_as_gen/matplotlib.pyplot.boxplot.html`.

S. Lai, N. W. Ruktanonchai, L. Zhou, O. Prosper, W. Luo, J. R. Floyd, A. Wesolowski, C. Zhang, X. Du, H. Yu, et al. Effect of non-pharmaceutical interventions to contain COVID-19 in China. *Nature*, 2020.

Q. Li, L. Bessell, X. Xiao, C. Fan, X. Gao, and A. Mostafavi. Disparate Patterns of Movements and Visits to Points of Interests Located in Urban Hotspots across US Metropolitan Cities during COVID-19. *arXiv preprint arXiv:2006.14157*, 2020.

Y. Liang, S. Gao, Y. Cai, N. Z. Foutz, and L. Wu. Calibrating the dynamic huff model for business analysis using location big data. *Transactions in GIS*, 24(3):681–703, 2020.

Y. Liu, Z. Sui, C. Kang, and Y. Gao. Uncovering patterns of inter-urban trip and spatial interaction from social media check-in data. *PloS one*, 9(1), 2014.

G. McKenzie and B. Adams. A country comparison of place-based activity response to covid-19 policies. *Applied Geography*, 125(12):102363, 2020.

G. McKenzie, K. Janowicz, S. Gao, J.-A. Yang, and Y. Hu. POI pulse: A multi-granular, semantic signature–based information observatory for the interactive visualization of big geosocial data. *Cartographica: The International Journal for Geographic Information and Geovisualization*, 50(2): 71–85, 2015.

G. Mohler, A. L. Bertozzi, J. Carter, M. B. Short, D. Sledge, G. E. Tita, C. D. Uchida, and P. J. Brantingham. Impact of social distancing during COVID-19 pandemic on crime in Los Angeles and Indianapolis. *Journal of Criminal Justice*, page 101692, 2020.

P. Newman and J. Kenworthy. The end of automobile dependence. In *The End of Automobile Dependence*, pages 201–226. Springer, 2015.

M. Painter and T. Qiu. Political beliefs affect compliance with COVID-19 social distancing orders. *Available at SSRN 3569098*, 2020.

Y. Pan, A. Darzi, A. Kabiri, G. Zhao, W. Luo, C. Xiong, and L. Zhang. Quantifying human mobility behaviour changes during the COVID-19 outbreak in the united states. *Scientific Reports*, 10(1):1–9, 2020.

L. S. Pun-Cheng. Distance decay. *International Encyclopedia of Geography: People, the Earth, Environment and Technology: People, the Earth, Environment and Technology*, pages 1–5, 2016.

A. Rundle, A. V. D. Roux, L. M. Freeman, D. Miller, K. M. Neckerman, and C. C. Weiss. The urban built environment and obesity in New York City: a multilevel analysis. *American Journal of Health Promotion*, 21(4_suppl):326–334, 2007.

SafeGraph. Places schema, 2020a. `https://docs.safegraph.com/docs`.

SafeGraph. Turn GPS data into store visit intelligence, 2020b. `https://www.safegraph.com/visit-attribution`.

J. Saha, B. B. Barman, and P. Chouhan. Lockdown for COVID-19 and its impact on pupil mobility in India: an analysis of the COVID-19 Community Mobility Reports, 2020. *Children and Youth Services Review*, page 105160, 2020.

Y. Shi and R. C. Eberhart. Empirical study of particle swarm optimization. In *Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406)*, volume 3, pages 1945–1950. IEEE, 1999.

A.-L. Sibony. The UK COVID-19 Response: A Behavioural Irony? *European Journal of Risk Regulation*, pages 1–8, 2020.

Smart Growth America. Measuring sprawl 2014, 2014. `https://www.smartgrowthamerica.org/app/legacy/documents/measuring-sprawl-2014.pdf`.

R. Squire. What about bias in the safegraph dataset?, 2020. `https://www.safegraph.com/blog/what-about-bias-in-the-safegraph-dataset`.

R. Suárez-Vega, J. L. Gutiérrez-Acuña, and M. Rodríguez-Díaz. Locating a supermarket using a locally calibrated Huff model. *International Journal of Geographical Information Science*, 29(2):217–233, 2015.

The National Academies of Sciences, Engineering, and Medicine. TRB Webinar: How Much Will COVID-19 Affect Travel Behavior?, 2020. `https://www.nationalacademies.org/event/06-01-2020/trb-webinar-how-much-will-covid-19-affect-travel-behavior#sectionContact`.

The New York Times. COVID in the U.S.: Latest Map and Case Count, 2020. `https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html#states`.

A. Tirachini and O. Cats. COVID-19 and public transportation: Current assessment, prospects, and research needs. *Journal of Public Transportation*, 22(1):1, 2020.

D. Wang, B. Y. He, J. Gao, J. Y. Chow, K. Ozbay, and S. Iyer. Impact of COVID-19 Behavioral Inertia on Reopening Strategies for New York City Transit. *arXiv preprint arXiv:2006.13368*, 2020.

Y. Wang, W. Jiang, S. Liu, X. Ye, and T. Wang. Evaluating trade areas using social media data with a calibrated huff model. *ISPRS International Journal of Geo-Information*, 5(7):112, 2016.

WHO. WHO Coronavirus Disease (COVID-19) Dashboard, 2020. `https://covid19.who.int/`.

P. Wojahn. Creating More Space for Safe Active Transportation and Outdoor Activity During COVID-19 and Beyond., 2020. https://www.nlc.org/article/2020/05/29/creating-more-space-for-safe-active-transportation-and-outdoor-activity-during-covid-19-and-beyond/.

World Health Organization. WHO Director-General's opening remarks at the media briefing on COVID-19, 2020. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020.

J. Wu, S. Smith, M. Khurana, C. Siemaszko, and B. DeJesus-Banos. Stay-at-home orders across the country, 2020. `https://www.nbcnews.com/health/health-news/here-are-stay-home-orders-across-country-n1168736`.

Y. Xiao, F. Wang, Y. Liu, and J. Wang. Reconstructing gravitational attractions of major cities in China from air passenger flow data, 2001–2008: a particle swarm optimization approach. *The Professional Geographer*, 65(2):265–282, 2013.

L. Zhang, S. Ghader, M. L. Pack, C. Xiong, A. Darzi, M. Yang, Q. Sun, A. Kabiri, and S. Hu. An interactive COVID-19 mobility impact and social distancing analysis platform. *medRxiv*, 2020.