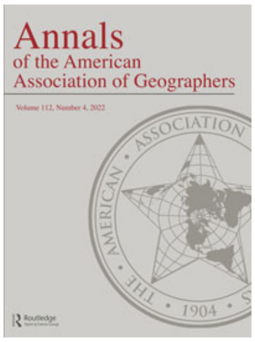

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The COVID-19 pandemic has profoundly reshaped urban mobility. During the lockdown, workers teleworked if possible and left home only for essential activities. Our study investigates the spatial patterns of essential travel and their socioeconomic differences during the COVID-19 lockdown phase in comparison with the same period in 2019. Using data from Columbus, Ohio, we categorized travelers into high, moderate, and low socioeconomic status (SES) clusters and modeled travel demand of SES clusters for both phases using spatially weighted interaction models. Then, we characterized the SES variability in essential travel based on frequently visited business activities from each cluster. Results suggest that disparities in travel across SES clusters that existed prior to COVID-19 were exacerbated during the pandemic lockdown. The diffused travel pattern of high and moderate SES clusters became localized and the preexisting localized travel pattern of low SES clusters became diffused. During the lockdown, the low and moderate SES clusters traveled mostly for work with long- and medium-distance trips, respectively, whereas the high SES cluster traveled mostly for recreational and other nonwork purposes with short-distance trips. This study draws some conclusions and implications to help researchers and practitioners plan for resilient and economically vibrant transportation systems in response to future shocks. *Key Words: equity, mobile phone data, O–D flow, social exclusion, spatial interaction.*

The COVID-19 pandemic has profoundly affected urban travel dynamics (Abu-Rayash and Dincer 2020; Huang, Li, Jiang, et al. 2020). U.S. cities experienced a reduction in travel demand during the COVID-19 lockdown in March and April 2020 (Huang, Li, Lu, et al. 2020; Chang et al. 2021). During these lockdowns, people were urged to travel only for essential activities as an effective measure for disease control (Paez 2020). For instance, the UK government allowed people to travel for out-of-home activities such as mandatory in-person work, shopping for necessary products and services, education and child care, medical reasons, outdoor exercise, and other activities (GOV.UK 2021). Although U.S. cities did not have similar guidelines, we assume that people experienced similar necessities for out-of-home activities during these lockdowns. Consequently, any travel during the COVID-19 lockdown can be considered essential to the traveler. Work-based out-of-home activities are essential to some people, to maintain their livelihood, as well as to enable our core economic activities. Meanwhile, travel to other out-of-home activities is sufficiently compelling to be conducted for some people during a time when out-of-home activities should otherwise be minimal. Based on this understanding, our study defines essential travel as the travel for any out-of-home activities that are important for individuals' life and work and cannot be done from home.

The notion of essential activity and travel is context dependent and varies by socioeconomic classes. For instance, work-based essential travel depends on the requirement of physical presence at the workplace. Employees with better work-from-home opportunities might find work-based travel less essential. In most cases, nonprofessional jobs do not provide such flexibilities and compel travel for employees (Dey et al. 2020). As discussed in previous literature, most nonprofessional workers belong to low-income and ethnic minority communities who might find work-based travel more essential due to fewer stay-at-home opportunities than others (Dingel and Neiman 2020; Mongey, Pilossoph, and Weinberg

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2020; Huang et al. 2021). Similarly, individuals of different socioeconomic classes might have different levels of essentiality to non-work-based travel (e.g., visiting retail stores and recreational facilities; Farber et al. 2011). Low-income communities might especially portray infrequent non-work-based travel due to their inflexible work schedule, inadequate spatial access to opportunities, and limited mobility (Lucas 2012, 2019; Kossek and Lautsch 2018). Therefore, the socioeconomic differences in essential travel also provide insights on the varying pandemic coping mechanisms of these communities that require travel during disruptions.

The study posits that the understanding of essential activity and travel varies by socioeconomic groups depending on their needs, patterns of work and non-work-based travel, and accessibility to services. We capture these varied patterns of essential travel based on the impact of COVID-19 lockdown on the derived travel demand of different SES groups. The purpose of this study is to characterize essential travel based on the changes in travel patterns between the pre-lockdown and lockdown phases. Our study has three objectives. First, it aims to explore the spatiotemporal changes in origin–destination (O–D) flows for travelers of different socioeconomic classes during the 2020 COVID-19 lockdown period compared with a 2019 reference period. Second, our study estimates derived travel demand to fulfill different business activities during these two phases. Third, this study identifies and characterizes essential trips based on the frequent destinations of travel flows.

We used a local form of spatial interaction (SI) modeling, a spatially weighted interaction model (SWIM), to analyze travel demand patterns between origins and destinations in a geographic system. The SI model reveals the influence of origin- and destination-specific attributes in determining the spatial structure of travel demand (Fotheringham and O'Kelly 1989; Fotheringham 2017; Oshan 2020). Past literature demonstrated numerous applications of SI models in understanding urban mobility (Marrocu and Paci 2013; Pourebrahim et al. 2018; Zhang, Cheng, and Jin 2019). SWIM, a subtype of SI models, considers the spatial heterogeneity in travel demands and calibrates the SI model for small-scale spatial units over geographic space (Kordi and Fotheringham 2016). In this study, we used an origin-specific, destination-focused SWIM to identify the variability in travel demand from the origins of different socioeconomic characteristics based on their destination attributes. We performed this analysis using mobility data from Columbus, Ohio, comparing travel demand by socioeconomic status (SES) for the local lockdown period (15 March–30 April 2020) to travel demand during the same period one year prior (15 March–30 April 2019).

Our study contributes to the understanding of socioeconomic differences and social equity in travel. By analyzing the spatial structure of essential travel patterns based on travelers' socioeconomic characteristics, our study provides several implications for designing inclusive and resilient transportation systems. First, it will help urban practitioners and researchers identify essential travel for business activities to prioritize network connectivity and mobility services that meet the needs of essential workers. Second, this study demonstrates a method to analyze the spatial distribution of essential trips that can be adopted in practice. Practitioners could use a similar approach to prioritize and facilitate need-specific transportation services, fulfill the mobility needs of underserved populations, and prepare for future disruptions. Finally, researchers and practitioners can apply this method to determine appropriate travel demand management strategies (e.g., telecommuting) for congestion relief.

Literature Review

The transportation literature covers a wide range of studies investigating socioeconomic differences in travel patterns and mobility needs. In this section, we synthesize past literature on transport-related social exclusion and its implications on both work travel and nonwork travel. Next, we review the applications of SI models in urban mobility studies.

Transport-Related Social Exclusion

Past studies have linked SES and transportation disadvantage: Low SES groups make fewer trips, travel shorter distances per trip, and are more likely to be socially excluded due to lower accessibility (Lucas 2012, 2019). The underlying causes of this transportation disparity include fewer mobility options (Lucas 2012, 2019; Mercado et al. 2012; Farber, Ritter, and Fu 2016); lack of accessibility to key destinations such as job centers, food stores, and health care facilities (Paez et al. 2010; Paez and

Farber 2012; Farber, Morang, and Widener 2014; Farber and Grandez 2017; Wei et al. 2017); lack of economic resources and time budget dedicated to discretionary activities; and inflexibility of working schedule (Blumenberg 2017). Such factors are big barriers for underserved communities to travel for essential purposes, such as employment, education, and health, as well as to participate in discretionary activities such as recreation. In the following subsections, we summarize evidence for travel disparity of underserved communities concerning work and nonwork travel.

Disparities in Work Travel

Low spatial access to job locations, accompanied by transportation inequalities, limits job opportunities for socially disadvantaged populations. Low-income people have fewer choices for both residence and job locations (Schleith, Widener, and Kim 2016). Although low-income people tend to reside in the core urban areas with higher job concentrations, they are often unable to access these jobs due to limited mobility choices (Wang 2003; Wenglenski and Orfeuil 2004). Recent studies, however, have identified the shift of low-income residences from inner-city to suburban areas, resulting in longer commuting time and lower access to opportunities, especially during the last few decades (1990–2013; Schleith, Widener, and Kim 2016; Hu 2017; Allen and Farber 2020). Thus, integrated transportation and social disadvantages are more prominent in suburban areas where car ownership often becomes necessary for low-income workers to access their workplaces (Hu 2017).

In terms of monetary and time constraints, limited budgets further exacerbate travel disparity for the low SES group. Kossek and Lautsch (2018) explored the scope of work–life flexibility for different occupation groups and found that lower level workers are more engaged in part-time jobs with limited workload controls, benefits, and vacations. Although part-time jobs have greater scheduling opportunities, employers offer the least flexibility to lower level workers to determine their work schedules and locations compared to the upper and middle-income classes (Kossek and Lautsch 2018). Dingel and Neiman (2020) estimated that 37 percent of U.S. jobs provide complete work-from-home opportunities; among those, professional, managerial, and corporate jobs offer higher scope for working from home. They also found a positive correlation between the median hourly wage and the percentage of jobs possible to be done from home. Mongey, Pilossoph, and Weinberg (2020) showed a strong positive correlation between "low work-from-home" and "high physical-proximity" jobs, which are mainly performed by the lower income population with a lower education level. Based on the American Time Use Survey and Occupational Information Network data sets, the percentage of work-from-home opportunity for professional jobs is 70 percent, financial jobs 78 percent, service jobs 31 percent, retail jobs 27 percent, recreation and food 13 percent, and education and health care 49 percent (Dey et al. 2020).

Limited transportation opportunity is a barrier to the economic independence and well-being of low SES groups. Blumenberg and Agrawal (2014) postulated that low-income people adopt numerous coping mechanisms to manage their transportation costs, such as minimizing travel distances to save expenses or prioritizing transportations expenditure over other basic needs such as food. In many cases, maintaining car expenses becomes essential for low-income people because their access to transit services is limited and reaching their jobs is nonnegotiable. In another study, Ettema et al. (2010) argued that the stress and time restrictions of planning daily trips and the associated restrictions on participating in social activities deteriorate both the cognitive and affective well-being of low-income people.

Disparities in Nonwork Travel

Nonwork travel patterns across SES groups generally depend on the accessibility to nonwork facilities (e.g., education, health care, recreation, and food locations) and resources dedicated to discretionary activities (e.g., money and time; Blumenberg 2017). Here we focus our review on frequent travel (e.g., on a weekly basis) such as recreational and food shopping trips.

In terms of recreational facilities, neighborhoods with minority populations and low SES groups tend to have lower access to outdoor recreational facilities and green space (e.g., parks, trails, golf courses, trees, agricultural land) than well-off neighborhoods (Moore et al. 2008; Park and Guldmann 2020). Cohen et al. (2013) indicated that cities with a similar number of parks in different SES neighborhoods have lower park usage in low-income neighborhoods than others due to fewer park amenities and activity opportunities.

Past studies have identified disparities in the spatial distribution of food stores with healthier options. Low-income and underserved neighborhoods tend to have fewer supermarkets and fresh food stores within proximity and comparatively more exposure to fast-food outlets (Moore et al. 2009; Thornton, Lamb, and Ball 2016). Many studies also found an association between food consumption patterns and exposure to an unhealthy food environment. In other words, residents of underserved neighborhoods are more likely to have a higher fast-food intake (Giskes et al. 2011; Thornton, Lamb, and Ball 2016; Janssen et al. 2018).

Applications of Spatial Interaction Models in Urban Mobility

The SI model is one of the core geographic approaches of investigating the complex spatial structure of flows of people, information, and goods. Application of SI models allows researchers to explain the organizational and distributional pattern of spatial flows considering the origin propulsiveness and destination attractiveness factors and the cost associated with the friction of distance between origin and destination (Fotheringham and O'Kelly 1989; O'Kelly 2015; Kordi and Fotheringham 2016; Fotheringham 2017; Oshan 2020). Past literature has applied SI models to explain human mobility patterns from different dimensions, such as migration, tourism, commuting, and accessibility.

In SI model-based mobility literature, socioeconomic attributes (e.g., population size, income, age group) are origin-specific determinants that can explain trip generation (Signorino et al. 2011; Marrocu and Paci 2013; Pourebrahim et al. 2018; Zhang, Cheng, and Jin 2019). Built environment attributes (e.g., number of opportunities available, density, quality of facilities) are common destination-specific determinants of travel demand attraction (Khadaroo and Seetanah 2008; Marrocu and Paci 2013; Dock, Song, and Lu 2015; Liu et al. 2016). Traditionally, the SI models generate one set of global parameters that reflects a generalized structure of SI for the entire study area. According to the spatial heterogeneity law of geography, however, spatial processes and phenomena vary across geographic space (Goodchild 2004). Therefore, global SI models often become inadequate in capturing the complex structure of spatial flows.

To accommodate spatial nonstationarity, researchers translated the concept of global SI models into local SI modeling techniques with the incorporation of spatial weights. The local models analyze the spatial flow structures for small-scale spatial units within the study area based on a geographically weighted function. Thus, local SI models explain any spatial variation in the effects of independent variables in determining flows. Nakaya (2001, 2002) integrated geographically weighted regression with SI models to analyze spatial flow characteristics specific to each origin. This method uses a local model for each origin based on the destinations as the calibration points. It considers a spatial kernel around each destination and assigns weights to the flows from origin to destinations, based on their distance from the destination. SWIM (Kordi and Fotheringham 2016), a localized form of SI model, uses a spatial weighting procedure similar to Nakaya (2001, 2002). SWIM is an advanced local SI calibration method that uses geographic locations within the study area as calibration points. Based on the criteria of localization and distance measuring, SWIM is categorized into three major branches: origin-focused models, destination-focused models, and flow-focused models. Few studies applied the SWIM models in identifying the socioeconomic determinants of O–D flow (Zhang, Cheng, and Jin 2019; Pulford, Cheng, and Jin 2020; Zhou et al. 2020).

SI models using the geographically weighted regression framework, however, account for spatial nonstationarity and are limited in addressing spatial dependence within the interaction data set. Past studies using this approach assumed that spatial flows are independent over space and adopted a fully local modeling technique where local models are calibrated separately around each origin and destination using spatial weights (Fotheringham, Brunsdon, and Charlton 2003; Nissi and Sarra 2011; Kordi and Fotheringham 2016; Zhang, Cheng, and Jin 2019; Pulford, Cheng, and Jin 2020; Zhou et al. 2020). There are other modified SI models to address spatial dependence in data sets using spatial modeling techniques like spatial lag autoregression (Fischer and Griffith 2008; LeSage and Fischer 2010) and eigenvector spatial filtering (Chun 2008; Fischer and Griffith 2008; Patuelli et al. 2015). These models, however, accommodate the locally varying effects with a set of global parameters and partially account for spatial heterogeneity (Fotheringham, Brunsdon, and Charlton 2003; Kordi 2013). To overcome the limitations of these two modeling approaches, Mello-Sampayo (2020) designed an integrated multilevel modeling technique that can account for both spatial autocorrelation and heterogeneity. Given the model complexities and our study purpose of understanding local variations in travel demand across SES groups, we consider SWIM a suitable approach for our study.

Methods

This study compares travel demand flows among O–D pairs in an urban area during the COVID-19 lockdown to the same period in 2019 across SES groups. First, we clustered origin block groups based on their SES characteristics and visualized changes in travel patterns based on the O–D flows during both periods. Second, we determined frequent business activities at the destinations in both periods using the SWIM approach. Finally, we compared the travel demand pattern to business activities in both periods to identify essential trips for different SES clusters.

Data

This study focuses on Franklin County, Ohio, where Columbus is located. The county consists of 887 block groups and is home to 1.3 million people (U.S. Census Bureau 2019). The lockdown phase in this study is from 15 March to 30 April 2020, whereas the pre-lockdown phase refers to the same period in 2019.

We used three types of data for our analyses: O–D flow, travelers' characteristics, and location of business activities. We obtained O–D flow data, average travel time, and travelers' socioeconomic characteristics at the census block group level from StreetLight (StreetLight Data, Inc. 2020). StreetLight collects trip data using location information and timestamp of mobile phone devices. They define origins and destinations as the start and end locations where the device remained stationary for a certain period and between which the mobile device was in motion. In addition, they determine the home and work location of travelers using timestamps and fuse the data set with associated socioeconomic information and trip purposes based on the home locations of travelers (StreetLight Data, Inc. 2018). Several transit agencies have reported StreetLight data collection and processing methods as accurate, which justifies StreetLight as a reliable data source (Turner, Tsapakis, and Koeneman 2020; Yang, Cetin, and Ma 2020). We collected points of interest data for business locations from SafeGraph (SafeGraph 2020). The data set includes geographic locations of business activities within our study area. We used twelve major business categories defined by the NAICS code (U.S. Census Bureau 2020) for this study and aggregated the total number of facilities for each business activity by block group. Table 1 provides the names and details for each business category (NAICS Association 2018).

For visual mapping of facilities, we used employee size and sales volume from InfoGroup (2019), educational facilities, hospitals, and open spaces (e.g., parks, golf courses, cemeteries, outdoor recreational facilities) from the Mid-Ohio Open Data platform (MORPC 2020). This visual analysis provides a general overview of the spatial distribution of facilities within the study area.

Identifying Socioeconomic Clusters

We classified the block groups into clusters based on the socioeconomic characteristics of the travelers originating from each block group. We determined the clusters using three variables from the data sets on both pre-lockdown and lockdown phases: (1) the percentage of travelers of different income groups (categorized into four classes), (2) the percentage of travelers of colors, and (3) trip purposes (categorized as home-based work trips, home-based other trips, and non-home-based trips). Then, we applied a hierarchical clustering analysis to identify clusters of a similar SES pattern. With this method, we sequentially merged block groups into clusters based on their similarity in travelers' attributes. We measured similarities between attributes using Manhattan distances and performed a complete-link clustering analysis (Contreras and Murtagh 2015).

Determining Frequently Visited Business Types

This study aims to understand the heterogeneous pattern of travel demand and its associated socioeconomic differences. We chose to apply an origin-specific destination-focused SWIM to capture the local

Table 1. Business categories used in this study

Business categories	NAICS code	Major establishments
Retail trade	44-45	Food and grocery stores, gas stations, health care stores, and stores for nonessential and luxury products
Finance and insurance	52	Banks, credit unions, mortgage and broker agencies, insurance companies
Rental and leasing services	53	Rental and leasing offices of real estate properties, cars, and other machineries and equipment
Professional, scientific, and technical services	54	Specialized jobs in engineering, software industries, legal services, scientific research, management, and consulting services
Educational services	61	Schools and training center for both formal and informal education
Health care and social assistance	62	Offices of specialized health care professionals and nurses, care facilities for families and individuals (children and elderly)
Arts, entertainment, and recreation	71	Parks and other outdoor recreational facilities, indoor sports centers, art and entertainment companies, museum, and historical sites
Accommodation and food services	72	Hotels, recreational campgrounds, restaurants and eating places, drinking places (bars)
Service jobs (except public administration)	81	Repair and maintenance shops (automobiles, electronics, other household goods), personal care services (salons and barbershops), and other nonprofessional organizations

variations in travel demand across different origins of SES clusters. The origins are the calibration points in the model because these are the likely home locations, especially during a pandemic, and broadly vary by SES. Flows to different destinations from the origin participate in the calibration process (Kordi and Fotheringham 2016). Along with the distance between origin and destination, the model evaluates destination characteristics as independent variables to identify the origin outflow determinants. Here, we used the number of different business activities at destinations as the destination attractiveness factor. For each origin, we assigned spatial weights to its observed flows based on the distance between that origin and its destinations. Then, we estimated the local model coefficients of that origin to represent the magnitude of influence of business activities on its travel demand.

We used the SWIM model to investigate the frequently visited business activities during the pandemic based on the travel flows from a specific origin (O) to different destinations (D) at the block group level. Our dependent variable is the travel demand between each O–D pair. We used the average daily O–D flow as the unit for measuring travel demand. Our independent variables included travel time between O–D pairs and the total number of facilities by business category at the destination block groups. Table 1 summarizes the business activity types used for this model. We developed separate models for 2019 and 2020 for each type of SES cluster. Equation 1 provides the mathematical formula for origin-specific destination-focused SWIM.

$$\begin{aligned} T_{ij} &= k_i g(a_j) f(c_{ij}) \\ g(a_j) &= a_j^{\gamma_i} \\ f(c_{ij}) &= \exp(\beta c_{ij}), \end{aligned} \tag{1}$$

where T_{ij} indicates the O–D flow from origin i to destination j; $g(a_j)$ is the attractiveness factor, measured as a power function of the number of facilities of a specific business type (a_j) at destination j. This factor assumes that the probability of a trip occurring between an O–D pair is directly related to the number of facilities available at the destination (Harris and Wilson 1978; Clarke 1985). $f(c_{ij})$ is the distance decay effect, estimated as an exponential function of the average travel time (c_{ij}) between origin i and destination j. The distance decay effect assumes that the probability of a trip occurring between an O–D pair is inversely related to its associated cost (e.g., duration, distance; Yin et al. 2019). Finally, k_i, γ_i, and β_i are the model parameters (to be estimated) specific to origin i (Harris and Wilson 1978; Kordi and Fotheringham 2016; Oshan 2016).

We used the Poisson-focused SWIM model as our tests showed that the O–D flows follow a Poisson distribution:

$$T_{ij} = \exp\left(k_i + \gamma_i \ln a_j + \beta_i c_{ij}\right). \tag{2}$$

We applied a squared Cauchy function to calculate the spatial weights of observed flows (Equation 3). This function also generates a similar bell-shaped curve as the Gaussian function with an extended tail. The O–D flow data are often skewed with considerably fewer flows from some origin. In these cases, the squared Cauchy function enables the model to use flows outside the bandwidth and fit the local model parameters with an inclination toward global parameters (Nakaya 2001; Kordi and Fotheringham 2016).

$$w_{ij} = \left[1 + \left(\frac{d_{ij}}{b}\right)^2\right]^{-2}, \qquad (3)$$

where w_{ij} denotes the weight of observed flow between origin i and destination j; d_{ij} is the Euclidean distance between the centroids of origin i and destination j; and b is the specified bandwidth. We used a fixed bandkaiwidth of 10 km, which is selected using a golden section search process with the lowest Akaike's information criterion (Kordi and Fotheringham 2016). We calculated standardized root mean square error (SRMSE) as an indicator of model fit, which indicates how closely the predicted values match the observed values. SRMSE closer to zero indicates a better model fit. To test the significance of differences in coefficients for the pre-lockdown and lockdown phases for different SES groups, we applied a two-sample Kolmogorov–Smirnov (KS) test and used the empirical cumulative distribution functions (ECDFs) derived from the distance decay effects and attractiveness functions (Equation 1) of SWIM models as inputs for this test.

Identifying Essential Trips

In our definition, an origin considers an activity center essential if it attracts trips from that origin before and during the lockdown, and the intensity (magnitude) of attraction is equal or higher in the lockdown phase. We identified essential trips for each origin based on their frequently visited destinations using local model coefficients from SWIM for each business activity. Specifically, we differentiated essential and nonessential trips based on the direction and magnitude of influence of a business type on flows. We characterized the essential trips to a business activity when local coefficients of origin block groups meet both of the following conditions:

1. The coefficient of business activity (destination) during the lockdown phase is significant and positive.
2. This coefficient remains stable or increases from the pre-lockdown phase to the lockdown phase.

Results

Socioeconomic Clusters of Travelers

Figure 1 presents the validation procedure of clustering. We applied the average silhouette method (Figure 1A) and the elbow method (Figure 1B) to identify the optimal number of clusters (Kaufman and Rousseeuw 2009). The figures show that the optimal number of clusters lies between two and four because the curves become flatter with clusters greater than four in both cases. Additionally, the dendrogram generated from clustering clearly depicts three different clusters within the data set (Figure 1C). Based on these results, we identify three SES clusters.

Table 2 shows the SES characteristics of the clusters. Based on these characteristics, we name clusters 1, 2, and 3 respectively as the high SES cluster (346 block groups), moderate SES cluster (363 block groups), and low SES cluster (178 block groups). The high SES cluster includes the highest percentages of high-income travelers (33 percent with an annual income of \$50,000–\$99,999 and 24 percent with more than \$100,000 annual income) and the lowest percentage of travelers of color (20 percent). In contrast, the low SES cluster includes the highest percentage of low-income travelers (28 percent of travelers with annual income less than \$20,000 and 37 percent of travelers with annual income \$20,000–\$49,999) and the highest percentage of travelers of color (55 percent). The moderate SES cluster represents a balanced mixture of travelers of all income groups and ethnic classes. Although we consider trip purposes in delineating the cluster, the results show little variation in trip purposes among the clusters.

The average daily origin outflow is highest for the moderate SES cluster (6,767 trips) and lowest for the low SES cluster (2,293 trips) during the pre-lockdown phase. The decline in outflow between the pre-lockdown and lockdown phases is lowest for the low SES cluster (41 percent) compared to the high SES (49 percent) and moderate SES (51 percent) clusters.

Figure 2 illustrates the spatial distribution of SES clusters. The map shows the dominance of block groups within the high SES cluster in west Columbus. Block groups within the low SES cluster are located in northeast, north-central, and southeastern Columbus. The rest of the block groups

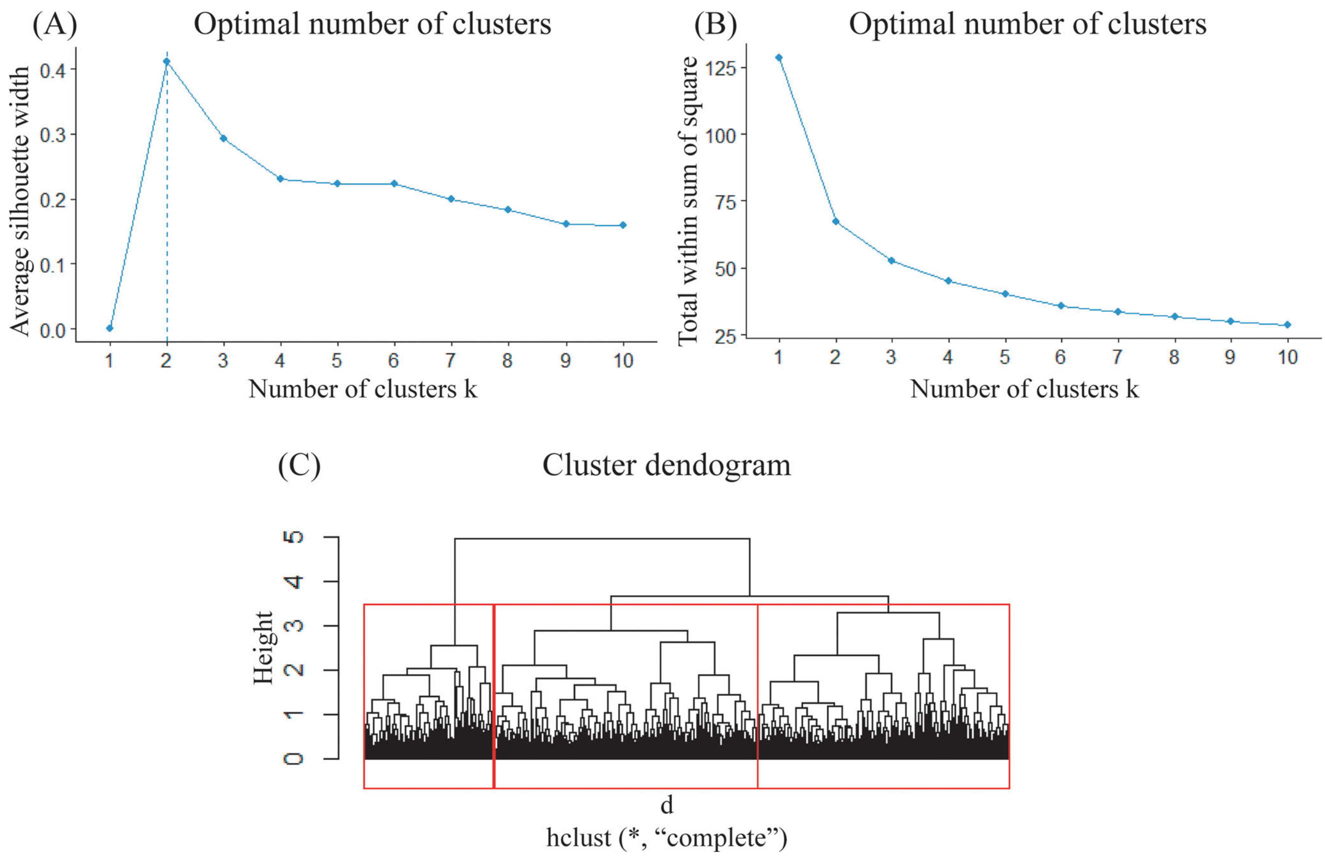

Figure 1. Validation for the optimal number of clusters: (A) average silhouette method, (B) elbow method, and (C) dendrogram created from the hierarchical clustering.

Table 2. Descriptive statistics of the average daily outflow and socioeconomic characteristics of clusters

	High SES cluster		Moderate SES cluster		Low SES cluster	
	M	*SD*	*M*	*SD*	*M*	*SD*
Average daily outflow (before COVID-19)	4,320	4,459	6,767	8,893	2,293	1,599
Average daily outflow (during COVID-19)	2,209	2,176	3,311	3,530	1,375	1,010
Percentage of household with income						
Less than $20,000	14	4	24	6	28	6
$20,000–$49,999	28	6	33	3	37	4
$50,000–$99,999	33	5	29	4	27	5
More than $100,000	24	10	14	4	9	3
Percentage of trip purposes						
Home-based work trip	13	4	12	4	11	2
Home-based nonwork trip	56	5	51	7	55	5
Non-home-based trip	31	6	37	6	34	6
Percentage of travelers of colors	20	7	31	6	55	8

Note: M = Mean; SD = Standard deviation; SES = socioeconomic status.

belong to the moderate SES cluster, including the west-central, southwestern, and south-central parts of Columbus. This marks a discernible east–west geographic divide in Columbus based on the SES of the city dwellers. This spatial segregation pattern is persistent over decades. The development of a north–south rail corridor in the nineteenth and early twentieth centuries and the construction of the U.S. interstate highway I-71 in the latter half of the twentieth century have exacerbated the clear

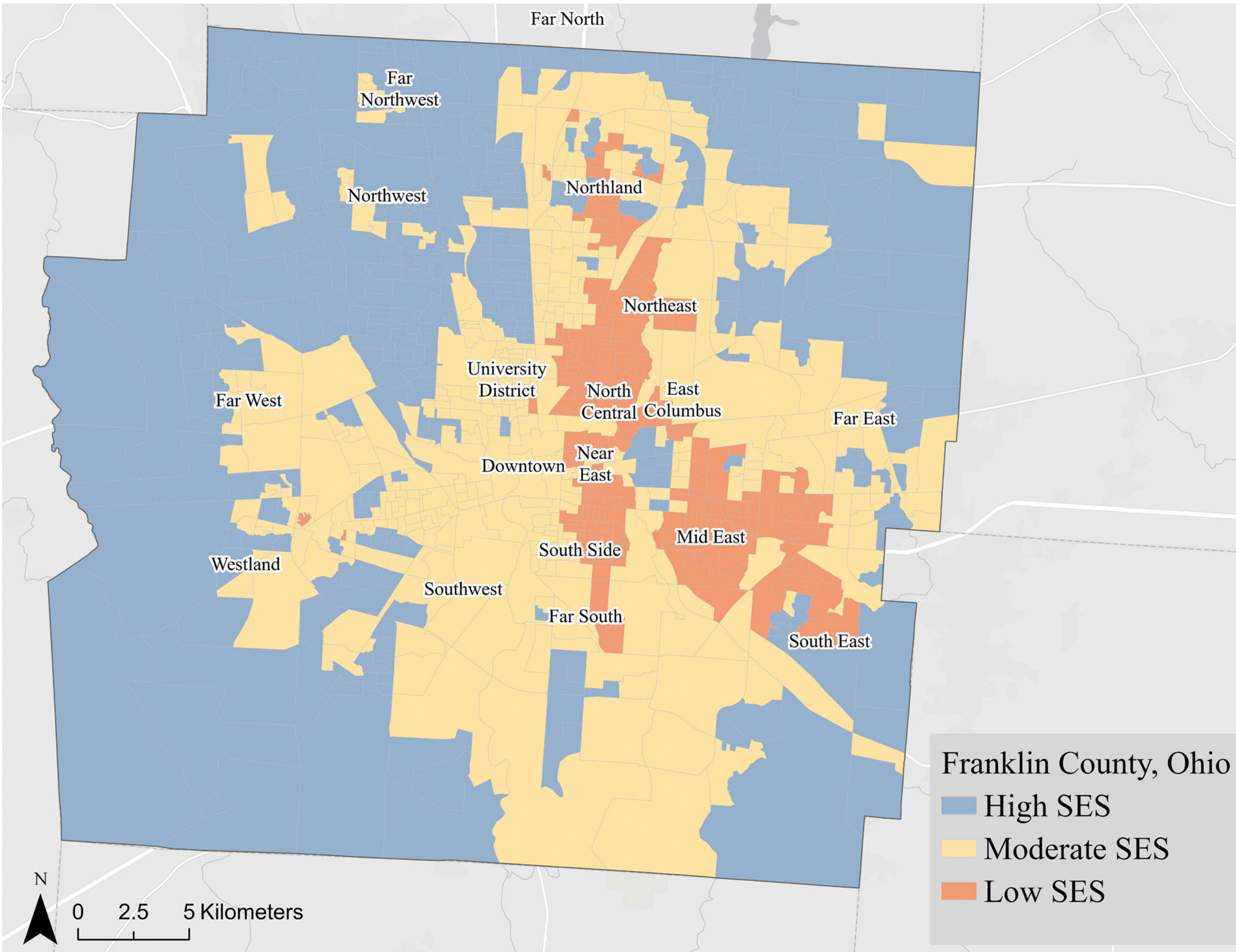

Figure 2. Franklin County categorized into clusters based on travelers' SES characteristics. SES = socioeconomic status.

boundary between the affluent and impoverished sections of the city (Hunker 2000; Campbell 2020; Lee et al. 2020).

Spatial Distribution of Facilities in the Study Area

Figure 3 illustrates the spatial distribution of business activities in the study area. Figure 3 indicates that most professional, rental and leasing, and service job opportunities with high employee capacity are concentrated in the Columbus central business district (CBD), located in west-central Columbus. Other job opportunities are mostly located in northwest Columbus. We refer to the high-capacity jobs concentrations in the northwest and northeast fringes of Columbus as the suburban business districts. Note that professional jobs are mostly located in the CBD, whereas most high-capacity rental and leasing and service jobs are located in the suburban business districts. Additionally, the business districts contain high and moderate SES block groups, providing better access to these communities. Low SES block groups are nearly void of professional jobs and rental and leasing offices and consist of mostly service jobs with low employee capacity.

Figure 4A shows that food and accommodation services are mostly concentrated near the business districts and the east of the study area. The elementary, middle, and high schools are more densified in the low SES areas (northeast Columbus) than in the remaining areas (Figure 4B). Most open spaces are located in the high and moderate SES clusters (large-scale parks in southwest, southeast, and northeast fringe and scattered small-scale parks and golf courses in the northwest fringe; Figure 5A). Finally, large-scale hospitals are located in central and northwest Columbus (Figure 5B).

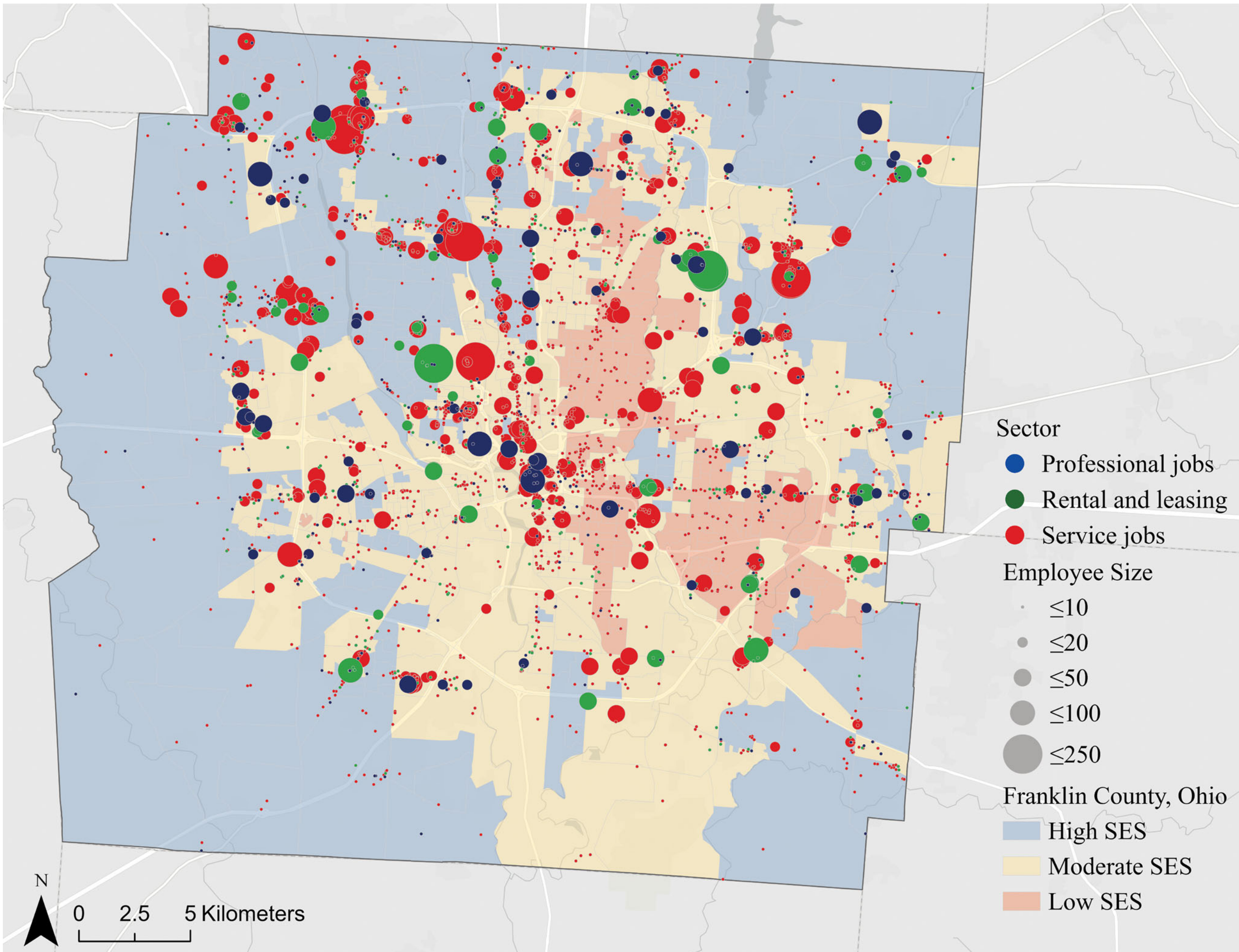

Figure 3. Distribution of professional jobs, rental and leasing offices, and service jobs across the study area (symbology scaled by employee size). SES = socioeconomic status.

Spatiotemporal Changes in O–D Flow

Figures 6, 7, and 8 compare the O–D flow of pre-lockdown (A) and lockdown phases (B) for high SES, moderate SES, and low SES clusters, respectively. There was a major decline in long-distance trips. Short-distance trips declined less compared to long-distance trips, especially for high and moderate SES clusters (Figures 6 and 7). Flows of high SES cluster show two major destinations for their long-distance travels during the pre-lockdown phase, which are the Columbus CBD and the suburban business district in northeast Columbus (Figures 6A and 7A). Flow to these two destinations also reduced substantially during the lockdown phase (Figures 6B and 7B). Also, the high SES cluster did not have any notable destination marked in the areas of the low SES cluster in both phases (Figure 6).

Along with the two major destinations from high SES block groups, moderate SES block groups had diverse destinations with heavy traffic inflows in the pre-lockdown phase (Figure 7A). In the lockdown phase, the travel demand from the moderate SES cluster to the high SES (northwestern) and low SES (southeastern) areas almost disappeared or significantly reduced (Figure 7B). It is worth noting that travel was already highly local for the low SES cluster in the pre-lockdown phase; COVID-19 had the smallest impact on travel demand patterns for this social group (Figure 8A). Although their frequent destinations in the northeast and east Columbus experienced a reduction in travel demand, the destinations and areas covered by this group for traveling purposes remained the same in the lockdown phase (Figure 8B).

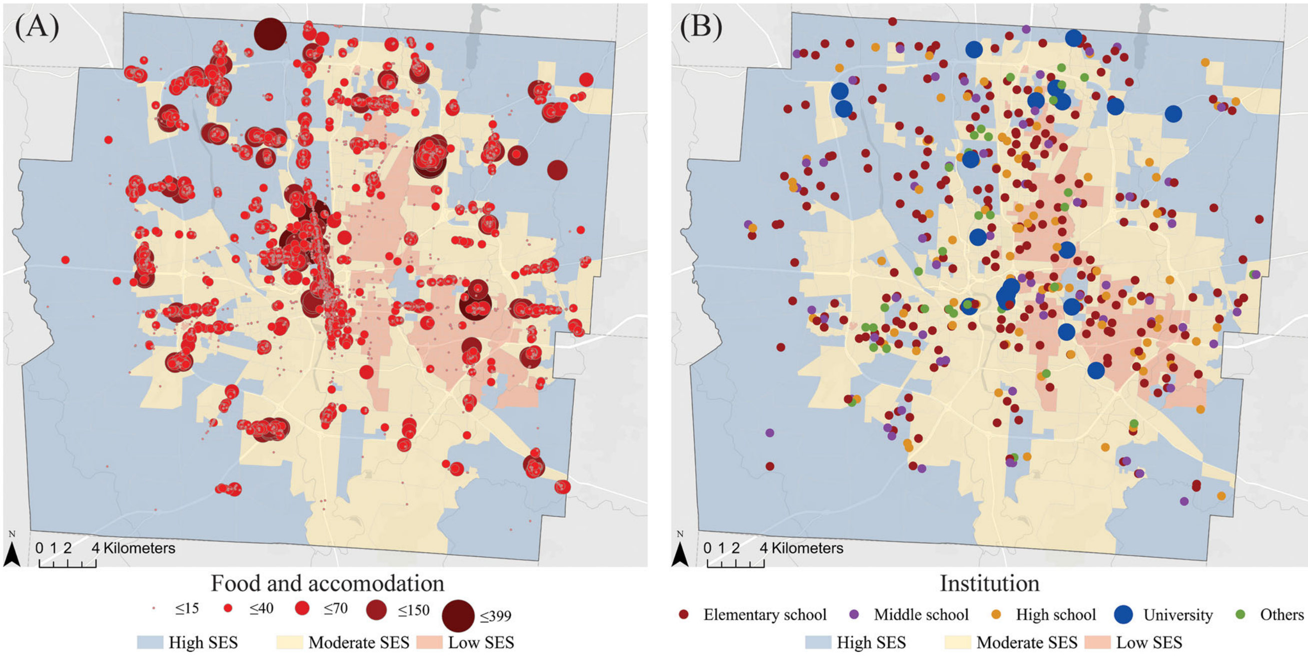

Figure 4. Distribution of business activities: (A) food and accommodation services (symbology scaled by employee size) and (B) educational institutions (categorized by their service type). SES = socioeconomic status.

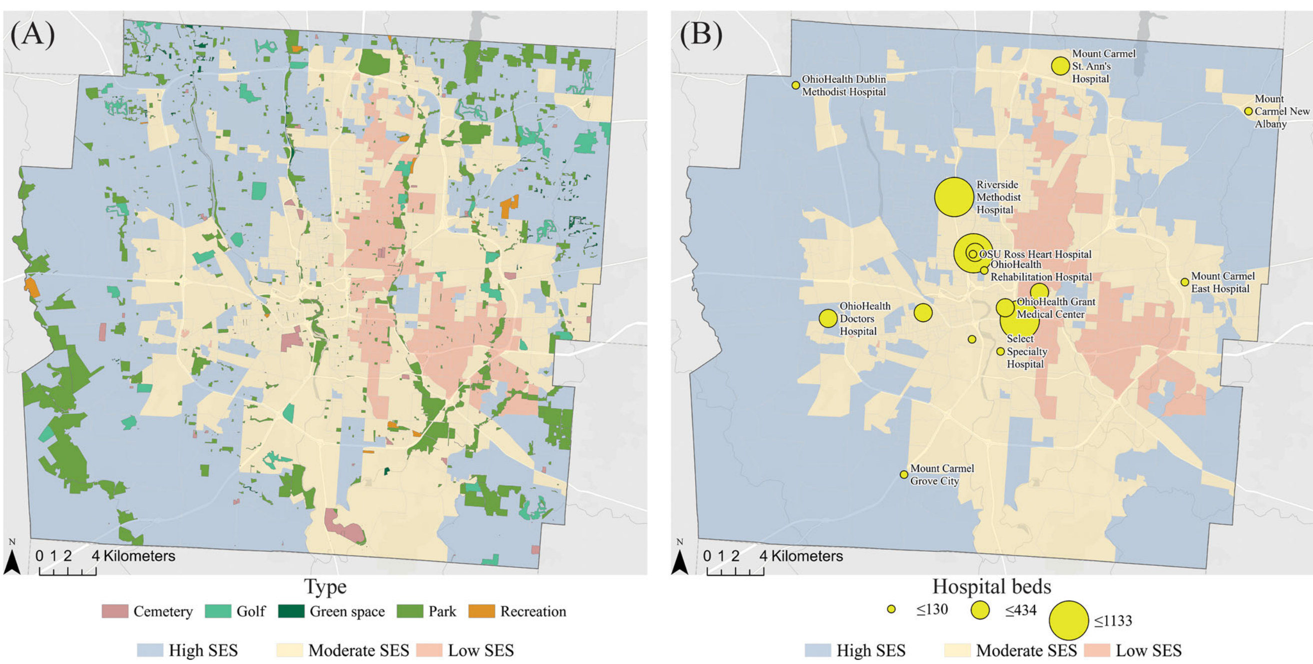

Figure 5. Distribution of business activities: (A) open spaces (e.g., parks, golf courses, cemeteries, outdoor recreational facilities) and (B) major hospitals. SES = socioeconomic status.

Frequent Business Activities by SES Clusters

Table 3 summarizes the significant local coefficients estimated for the origin block groups from the SWIM for the pre-lockdown and lockdown phases, categorized by SES clusters. Our model results indicate that all types of business, except financial services, were the frequent destinations from high SES block groups. In the lockdown phase, both retail and financial services received fewer visits. Based on the percentage of significant local coefficients in our SWIM models, we identify that

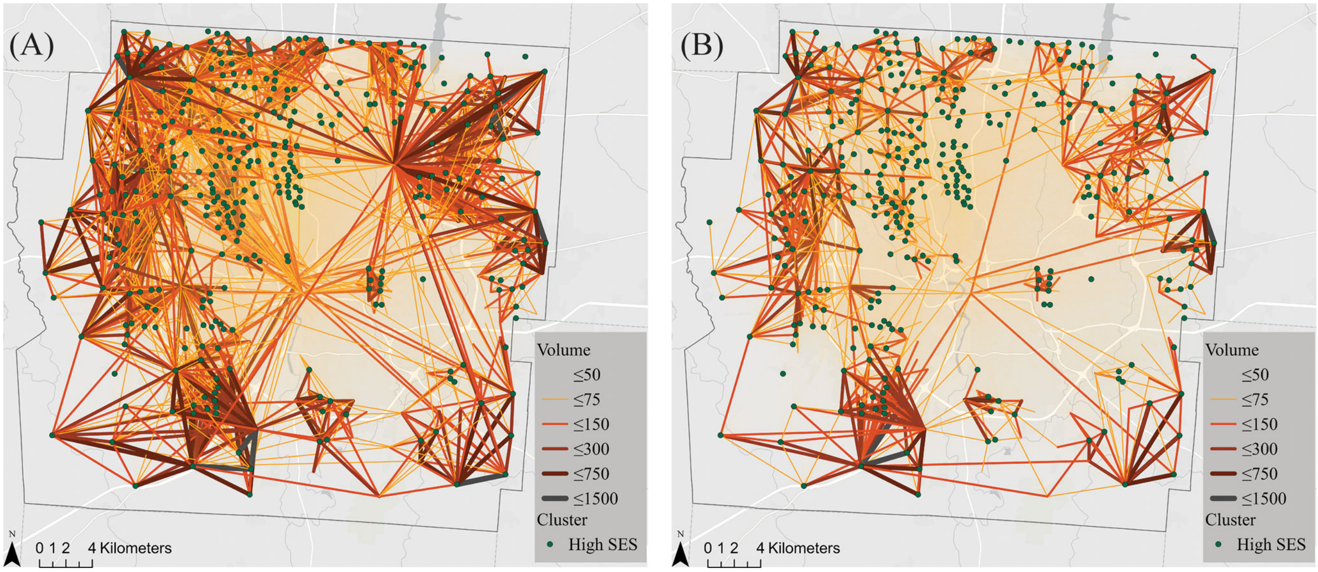

Figure 6. Origin–destination flow of high SES block groups: (A) pre-lockdown phase and (B) lockdown phase. SES = socioeconomic status.

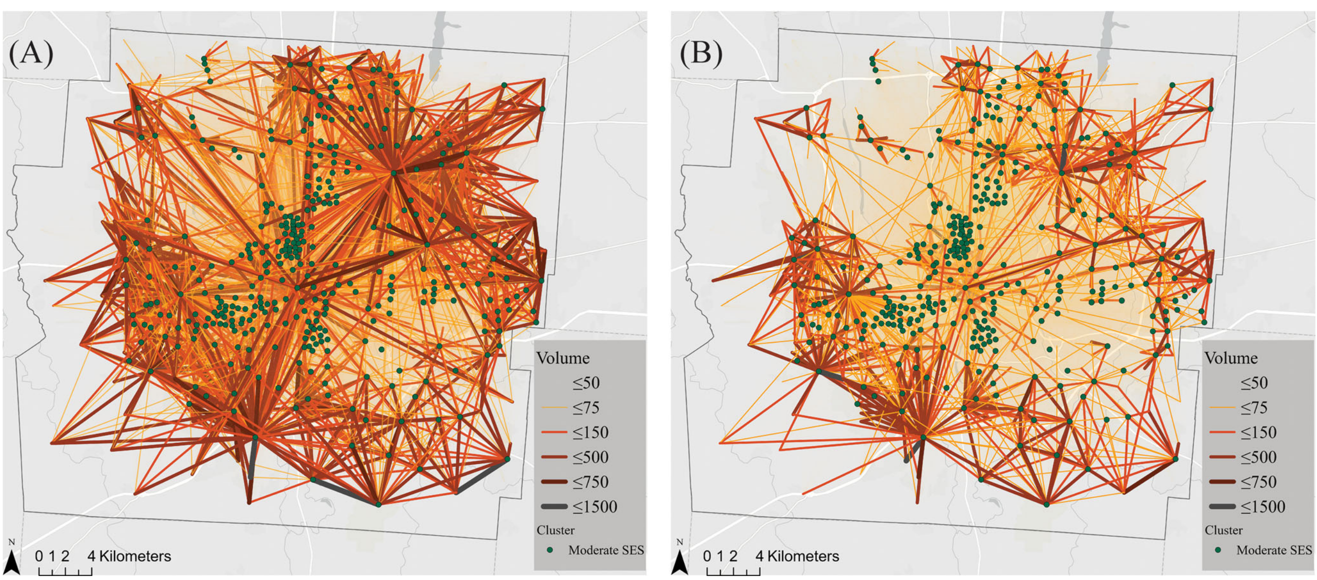

Figure 7. Origin–destination flow of moderate SES block groups: (A) pre-lockdown phase and (B) lockdown phase. SES = socioeconomic status.

residents of high SES block groups frequently visited educational (84 percent of all high SES block groups), recreational (74 percent), professional (71 percent), and health care facilities (70 percent) during the pre-lockdown phase. During the lockdown phase, their frequency of visits to these facilities was reduced, especially for educational facilities (61 percent). They maintained a high frequency of travel to recreational facilities (69 percent), professional services (66 percent), rental and leasing (64 percent), and health care facilities (61 percent), however; travel demand to these facilities was higher compared to the visits to the other business activities during the lockdown phase.

The frequently visited business types of the moderate SES cluster are similar to those of the high SES cluster in both pre-lockdown and lockdown phases. The overall travel demand declined, however. Travelers from the moderate SES cluster frequently visited all types of business facilities in the pre-lockdown phase (>60 percent of moderate SES block groups have significant local coefficients in

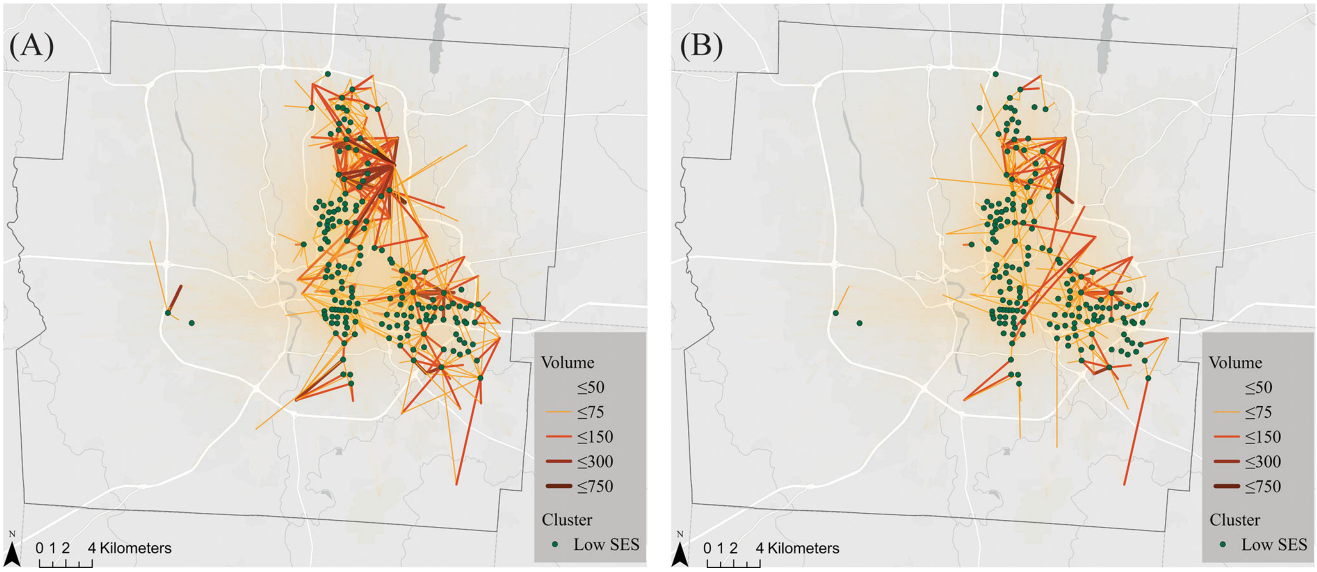

Figure 8. Origin–destination flow of low SES block groups - A) pre-lockdown phase and B) lockdown phase. SES = socioeconomic status.

the models for all business types). In particular, the moderate SES cluster frequently visited education (79 percent of all moderate SES block groups in pre-lockdown, 64 percent during lockdown), rental and leasing (79 percent in pre-lockdown, 76 percent during lockdown), and recreational facilities (73 percent in pre-lockdown, 63 percent during lockdown) compared to other business types. This cluster also frequently visited professional services, service jobs, and food and accommodation facilities in both phases. Among all of these facilities, the changes in the visit frequency are lower for professional services (65 percent to 62 percent), rental and leasing (79 percent to 76 percent), and service jobs (70 percent to 60 percent) between lockdown and pre-lockdown phases.

For low SES block groups, all business types except recreational and financial facilities were frequent destinations in the pre-lockdown phase. In the lockdown phase, retail and health care facilities, in addition to the recreational and financial facilities, were no longer frequent destinations of the low SES cluster. This cluster frequently visited service jobs (62 percent), education (60 percent), rental and leasing (58 percent), and food and accommodation (51 percent) facilities in the pre-lockdown phase. During the lockdown phase, their travel demand to these frequently visited facilities slightly declined, except for food and accommodation (37 percent in the lockdown phase). Professional services also appear as one of the frequently visited business activities for this cluster during the lockdown phase.

Identifying Essential Trips Based on Business Types at Destinations

Our results from the two-sided, two-sample KS tests indicate significant differences in the pre-lockdown and lockdown ECDFs for distance decay effects and attractiveness factors estimated from the SWIM model. We provide the D-statistic of KS tests in the Appendix to represent the maximum vertical distance of upward or downward shift between the respective ECDFs (Massey 1951). Figure 9 illustrates the ECDFs of distance decay effects and attractiveness factors to business activities to explain the direction of changes between the pre-lockdown and lockdown phase. The *x*-axis represents the distance decay effect or attractiveness factor, and the *y*-axis represents the cumulative percentage of trips. The distance decay effect visualizes the discounting effects of travel time on travel demand depending on the origin-specific distance decay parameters. The ECDFs of the distance decay effect indicate an upward shift in the lockdown phase from the pre-lockdown phase, suggesting a stronger discounting effect of travel time on trips.

An attractiveness factor greater than one explains the compounding effect of a particular business activity at destinations on generating trips from a specific origin, whereas an attractiveness factor less than one accounts for the discounting effect of business activities at destinations on travel demand of that origin. Moreover, an upward shift in the ECDF

Table 3. Means and standard deviations of the significant local coefficients estimated from the spatially weighted interaction model

	Pre-lockdown phase								
	High SES cluster			Moderate SES cluster			Low SES cluster		
	M coefficient	*SD*	Significant local coefficient (%)	*M* coefficient	*SD*	Significant local coefficient (%)	*M* coefficient	*SD*	Significant local coefficient (%)
Intercept	422	1,801	100	455	1,577	100	37	92	100
Average trip length	0.998	0.001	100	0.998	0.001	99	0.999	0.000	98
Facility type									
Recreation	**1.069**	**0.111**	**74**	**1.046**	**0.117**	**73**	0.934	0.120	45
Professional	**1.074**	**0.255**	**71**	1.067	0.178	65	1.052	0.213	47
Health care	**1.014**	**0.020**	**70**	1.014	0.014	66	1.006	0.020	34
Retail	1.010	0.009	46	1.007	0.013	62	1.008	0.007	38
Food and accommodation	1.020	0.032	65	**1.023**	**0.021**	**70**	**1.024**	**0.023**	**51**
Finance	0.964	0.055	69	0.941	0.038	72	0.950	0.036	44
Education	**1.197**	**0.153**	**84**	**1.193**	**0.181**	**79**	**1.142**	**0.067**	**60**
Rental and leasing	1.101	0.154	64	**1.098**	**0.149**	**79**	**1.096**	**0.104**	**58**
Service jobs	1.008	0.058	65	**1.013**	**0.047**	**70**	**1.053**	**0.030**	**62**
Goodness of fit									
SRMSE	M = 0.025, *SD* = 0.009, median = 0.025 (IQR: 0.019, 0.032, minimum = 0.003, maximum = 0.071)								
	Lockdown phase								
	High SES cluster			Moderate SES cluster			Low SES cluster		
	M coefficient	*SD*	Significant local coefficient (%)	*M* coefficient	*SD*	Significant local coefficient (%)	*M* coefficient	*SD*	Significant local coefficient (%)
Intercept	104	503	100	123	517	100	14	38	100
Average trip length	0.999	0.001	89	0.999	0.001	88	0.999	0.000	67
Facility type									
Recreation	**1.032**	**0.148**	**69**	**1.011**	**0.146**	**63**	0.884	0.143	45
Professional	**1.142**	**0.330**	**66**	**1.124**	**0.243**	**62**	**1.097**	**0.260**	**46**
Health care	**1.010**	**0.026**	**61**	1.013	0.022	49	0.999	0.032	36
Retail	0.996	0.032	37	1.002	0.025	42	0.992	0.027	25
Food and accommodation	1.005	0.052	58	1.022	0.034	60	1.033	0.061	37
Finance	0.974	0.088	59	0.941	0.062	62	0.947	0.079	38
Education	**1.105**	**0.194**	**61**	**1.090**	**0.165**	**64**	**1.124**	**0.125**	**44**
Rental and leasing	**1.123**	**0.196**	**64**	**1.112**	**0.163**	**76**	**1.157**	**0.109**	**52**
Service jobs	1.018	0.073	59	1.020	0.055	60	**1.060**	**0.045**	**54**
Goodness of fit									
SRMSE	M = 0.036, *SD* = 0.01, Median = 0.035 (IQR: 0.029, 0.041, minimum = 0.008, maximum = 0.083)								

Note: Mean coefficients are estimated as the average of the exponential values of significant local coefficients. Significance level: $p \leq 0.05$. $n_{\text{high SES}} = 364$ block groups, $n_{\text{moderate SES}} = 363$ block groups, $n_{\text{low SES}} = 178$ block groups. Business activities with frequent visits from SES clusters are shown in bold. M = Mean; SD = Standard deviation; SES = socioeconomic status; SRMSE = standardized root mean square error.

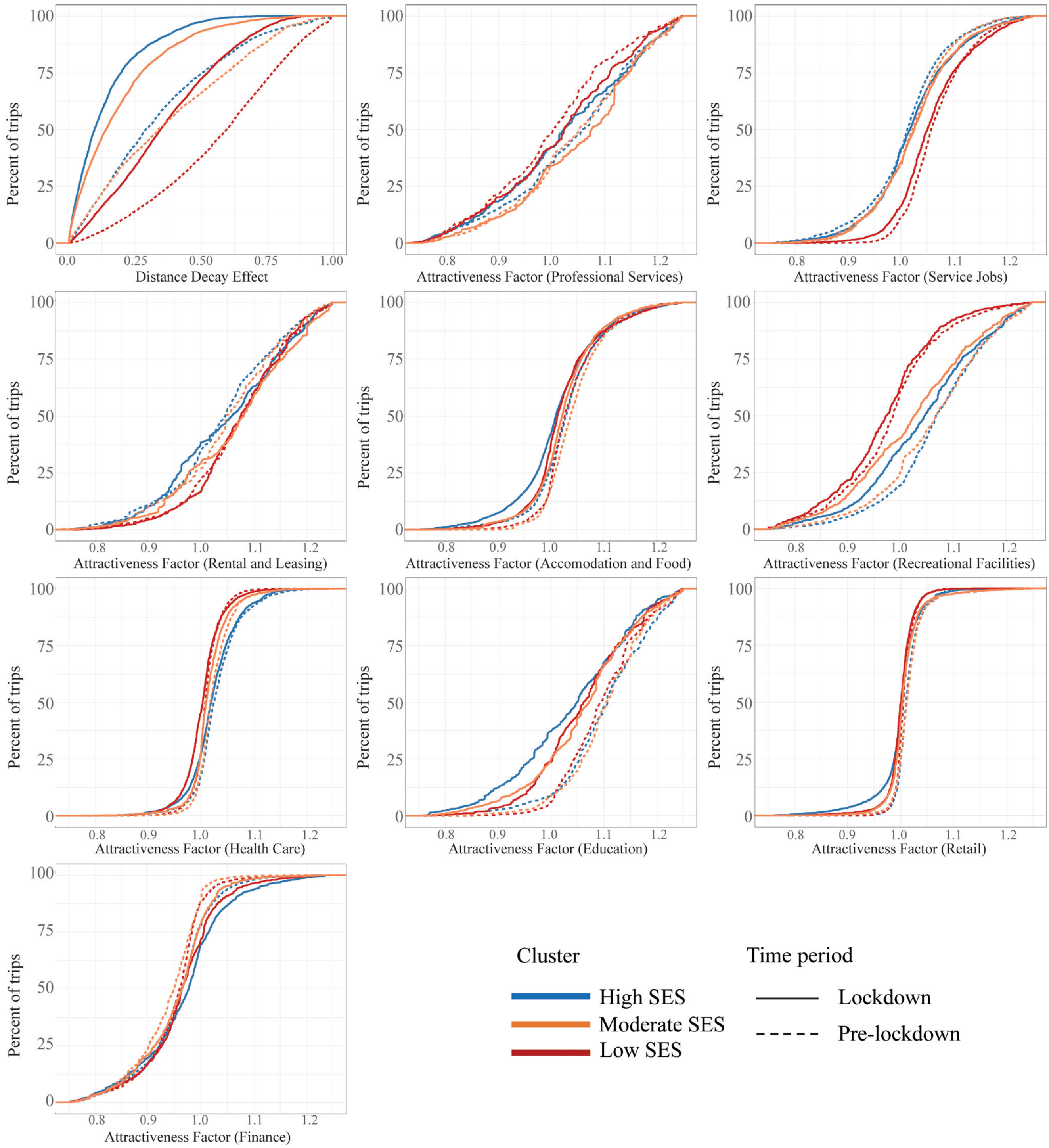

Figure 9. Empirical cumulative distribution functions (ECDFs) of distance decay effect and attractiveness factors for different SES clusters in the lockdown and pre-lockdown phases. SES = socioeconomic status.

of attractiveness factors indicates a decrease in attractiveness and a downward shift suggests an increase in attractiveness. Figure 9 depicts an increase in the overall attractiveness to professional services, service jobs, rental and leasing, and financial services and a decrease in the overall attractiveness of accommodation and food facilities, recreational facilities, health care, education, and retail services from the pre-lockdown phase to the lockdown phase with varying effects for different SES clusters.

The results suggest that high and moderate SES clusters present higher travel demand to professional

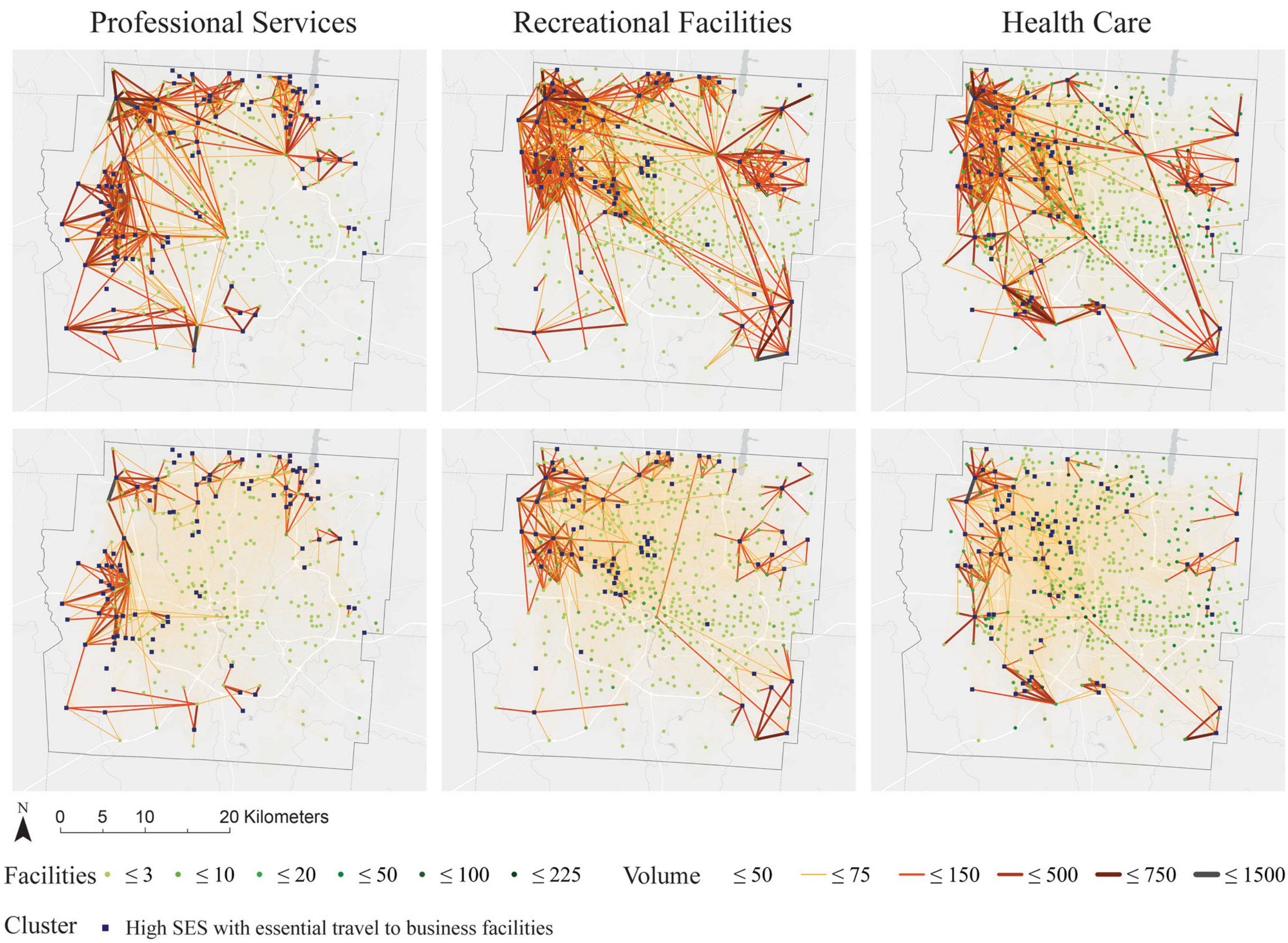

Figure 10. Average daily origin–destination flow from the high SES origins with essential travel to business facilities during pre-lockdown phase (top row) and lockdown phase (bottom row). SES = socioeconomic status.

services in both phases than the low SES cluster. In addition, recreational and health care facilities impart a higher compounding effect in generating trips from the high SES cluster than others. Similarly, the compounding effect of rental and leasing facilities has a stronger influence on the travel demand from the moderate SES cluster, with a substantial increase in influence in the lockdown phase.

Service jobs have a higher compounding effect on travel demand from low SES cluster in both phases. Most trips from high and moderate SES also occur, however, when service jobs display a compounding effect. In addition, accommodation and food facilities and educational facilities show similar or higher compounding effects on the low SES cluster than the moderate and high SES clusters in the lockdown phase. Financial services and retail facilities perform as discounting factors for most trips from all clusters, however.

Based on the summary findings of SWIM models and ECDFs, we have selected three business activities for each SES cluster to visualize essential travel patterns. According to our definition, all origins from an SES cluster might not present essential travel to the specified activities. Hence, we used our criteria of determining essential trips to identify the origins with essential travel to different business activities. Figure 10 presents the O–D flows of essential trips from the high SES cluster to professional, recreational, and health care facilities. Figure 10 shows that the origins with essential trips to professional services used to visit the business districts, mostly with shorter distance trips and fewer longer distance trips to the Columbus CBD during the pre-lockdown phase. Interestingly, travelers showing essentiality of recreational facilities used to travel long distances to visit the business districts at central Columbus and northeast Columbus. Travelers with

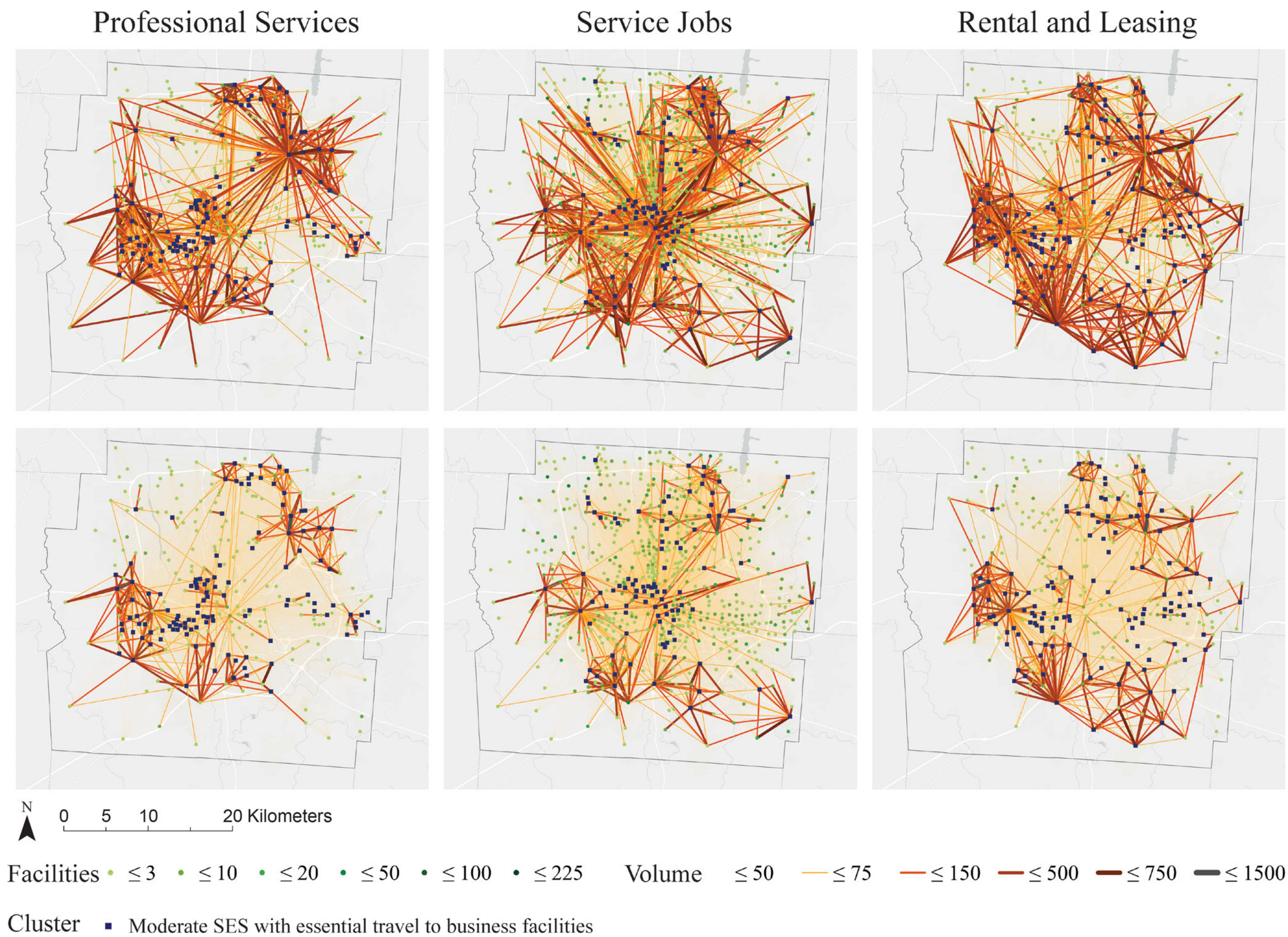

Figure 11. Average daily origin–destination flow from the moderate SES origins with essential travel to business facilities during pre-lockdown phase (top row) and lockdown phase (bottom row). SES = socioeconomic status.

essential travel to health care also had a similar long-distance travel pattern to the destinations with major hospital locations. In all cases, the long-distance travel demand substantially reduced during the lockdown phase. Especially for professional services, we observe O–D flows mainly traveling to their nearby suburban business districts. The travel demand to visit nearby recreational facilities and health care facilities was also significantly higher than visiting these facilities at distant locations.

Figure 11 presents the O–D flows of essential trips from the moderate SES cluster to professional jobs, service jobs, and rental and leasing facilities. The moderate SES cluster showing essential travel to professional services is mostly located on the affluent side of the city (west Columbus). In contrast, most clusters with essential trips to service jobs are located in the impoverished part of the city (east Columbus). A long-distance travel pattern was evident in all cases in the pre-lockdown phase. The business districts were the main destinations for travelers with essential trips to professional services. These travelers used to travel long distances, especially to visit Columbus CBD and the suburban business districts in the west where most of the professional jobs are concentrated. Similarly, travelers with essential trips to rental and leasing used to travel long distances to visit the Columbus CBD and the business destinations in the northeast and southwest areas with higher concentration of rental and leasing offices. Travelers with essential trips to service jobs show a diffused long-distance travel pattern in all directions. In the lockdown phase, long-distance travel demand decreased significantly for visiting professional services and rental and leasing services. The long-distance travel demand to visit service jobs at the CBD remained high in the lockdown phase, however.

Figure 12 presents the O–D flows of essential trips from the low SES cluster to service jobs,

Figure 12. Average daily origin–destination flow from the low SES origins with essential travel to business facilities during pre-lockdown phase (top row) and lockdown phase (bottom row). SES = socioeconomic status.

accommodation and food, and educational facilities. As reflected in Figures 3, 4, and 5, the distribution of any business activities within this region is very low. Also, low SES travelers mostly visited nearby areas in both phases. The majority of low SES travelers with essential trips to service jobs used to visit the business district on the east and other nearby service job destinations. Similarly, most travelers with essential trips to food services and education used to visit nearby facilities. In all cases, the travel pattern became more diffused in the lockdown phase. In particular, the destinations from the origins with essential trips to service jobs became more scattered within many regions of Columbus in the lockdown phase than they were in the pre-lockdown phase. Although the O–D flow was comparatively lower than for other SES groups, we observe that low SES people had a wider spatial coverage of essential travel in the pandemic phase than their regular travel in the nonpandemic phase.

Discussion

Our study investigates the differences in essential travel by socioeconomic groups for Columbus, Ohio. We classified origins into three SES clusters: high, moderate, and low SES. We developed SWIM to model the O–D flow of these SES clusters in the lockdown phase in 2020 and the same time period in 2019. Finally, we identified the frequently visited destinations by business activity types for each cluster and compared the results to investigate the variation in essential travel by different SES clusters.

The results lend support to the existence of transport-related social exclusion and spatial segregation in the travel pattern among the SES groups. Similar to the previous studies (Lucas 2012, 2019; Blumenberg and Agrawal 2014), our visualization of spatiotemporal changes in travel demand and SWIM model results consistently show localized travel pattern of the low SES cluster with short-distance trips and low trip frequency before the COVID-19 pandemic. In contrast, the high and moderate SES travel patterns were diffused with a higher number of long-distance trips, especially to visit the business districts within the city. Low SES travelers made fewer trips, possibly due to lower spatial access to opportunities, as suggested in previous studies (Wang 2003; Schleith, Widener, and Kim 2016; Allen and Farber 2020). Unavailable or inefficient transit services might have impeded long-distance travel for low SES people (Farber and Grandez 2017; Wei et al. 2017). In addition to the existing, long-term transportation disadvantages, COVID-19 has highlighted the travel needs of low SES people. They exhibited significantly less reduction in their travel demand than their high and moderate SES counterparts during the lockdown phase. Fewer work-from-home opportunities are perhaps a key reason forcing low SES people to travel during the disruption.

During the COVID-19 lockdown, travel restrictions have made the travel patterns localized and segregated, especially for the high SES group. High SES travelers, who used to travel longer for both work and nonwork purposes in 2019, were able to limit their travel to nearby local destinations only in the lockdown phase. Better job flexibility is a key contributor to these changes in travel patterns. High SES travelers exhibit essential travel needs to professional services that facilitate online work opportunities in 70 percent of cases (Dey et al. 2020). Health care service is perhaps another essential job destination for the high SES cluster because they reflect essential travel to major hospital locations during the lockdown. In addition to work trips, high SES travelers portray essential travel to recreational facilities. During the lockdown, when all indoor facilities were closed except outdoor parks and trails (Keren 2020), high SES travelers had the advantage of visiting these facilities due to better access (Cohen et al. 2013; Park and Guldmann 2020). Hence, the high SES cluster opted for recreational facilities to relieve lockdown stress and visited them more frequently than usual (Keren 2020).

The moderate SES travelers also localized their travel with a smaller magnitude of change in long-distance trips than the high SES group. The moderate SES group generates more work-based essential travel than other SES groups due to their ability to engage in various occupation types. Our findings suggest that essential travel of moderate SES travelers is linked to professional jobs, rental and leasing, and service jobs. Both frequency and extent of essential travel to professional services are higher for the moderate SES group than the high SES group. This implies that high SES professional workers are employed in job positions with better work-from-home opportunities than moderate SES professionals. In addition, we find travel to service jobs and rental and leasing offices essential for moderate SES groups. We suggest that travelers visiting rental and leasing offices are mainly construction workers. Twenty-nine states of the United States, including Ohio, considered construction essential work and allowed the continuation of construction projects during the COVID-19 lockdown period (Kovac 2020; Weiker 2020). In addition, only 31 percent of the service jobs facilitate work-from-home opportunities (Dey et al. 2020), which supports the continuation of long-distance travel of service workers from moderate SES groups.

In contrast to the high and moderate SES groups, the low SES group with a localized travel pattern in 2019 experienced a relatively lower reduction in travel demand with a more diffused (i.e., long-distance) travel pattern in 2020. This diffused travel pattern of the low SES cluster is particularly evident for their essential visits to service jobs. As suggested by Kossek and Lautsch (2018) and Dingel and Neiman (2020), most low SES people are engaged in multiple nonprofessional jobs with lower hourly wages and lower flexibility in work location and schedule. Therefore, they continued to travel to multiple job destinations during the lockdown phase. In many cases, these nonprofessional, informal workers lost their jobs and switched to other job locations, which might explain the diffused travel pattern of the service workers from the low SES group.

Our study also identifies accommodation and food facilities as essential travel destinations for the low SES cluster. During the pandemic, large-scale firms (e.g., fast-food chain shops) were fully operational due to better provisions of drive-throughs, take-out, and curbside deliveries, compared to small-scale independent restaurants (e.g., dine-in restaurants; Keysser 2020). Therefore, we hypothesize that these essential travelers mostly represent the workers and consumers of fast-food stores. This finding reiterates the dependency of the low SES group on fast-food restaurants for their livelihood and their food needs

(Thornton, Lamb, and Ball 2016; Janssen et al. 2018). We also identify essential travel to educational services for the low SES cluster. The continuation of meal programs in schools facilitated by the U.S. Department of Agriculture might explain the travel needs of low SES people to educational facilities (Dunn et al. 2020). Thirty-five million people nationwide and 40 percent of Ohio schoolchildren depend on this service (Neese 2020). Thus, essential travel of low SES groups to education facilities further emphasizes the home locations of potential beneficiaries of such meal programs.

Conclusions

This study characterizes the socioeconomic dynamics of essential travel: travel that occurred during a pandemic-induced business closure, travel restrictions, and advisories. The study uses travel patterns of Columbus, Ohio, as a case study. Understanding the essential travel characteristics will help urban researchers and practitioners redesign transportation systems that better serve the functionality of the economy and enhance resilience for future shocks. This study serves as a guideline for identifying spatial locations of transportation infrastructure and service to facilitate the travel of the essential workforce. It also assists urban practitioners to identify the demographic segment and spatial distribution of the higher SES population who could adopt telecommuting as a congestion relief strategy. Urban researchers and practitioners should take these essential travel characteristics into account to ensure efficient mobility services connecting the essential travelers and the activities inducing their travel. The study will also allow them to prioritize strategies accommodating need-specific transportation interventions as a means of promoting transportation equity.

The study has several limitations. First, our study is limited to the assumption that trips with multiple destinations (i.e., chained trips) are counted as separate trips in the data set. Second, our findings on essential travel to facilities are based on the correlation between the spatial distribution of facilities and O–D flow to the destination block groups, estimated from SWIM. O–D flow presented here does not reveal the actual visit to a specific facility. Third, our study assumes that travelers originating from the same block group possess the same essential travel needs. This assumption is subject to the ecological fallacy that might cause inaccurate estimation of results for outliers. For example, few high-income people might reside in the low SES cluster, with different travel essentialities than the other residents. Our study does not reflect these outliers. Fourth, our model is limited in its ability to account for network autocorrelation and assumes the flow data set as spatially independent.

Future studies might advance this research using location-specific O–D flow data to explore the travel pattern specific to business activities. Researchers might consider additional factors such as activity duration and travel modes in modeling the travel demand pattern to better explain the differences between work-based and non-work-based essential travel across SES groups. The study portrays essential travel as an outcome of travelers' revealed activity pattern and discusses the findings in light of the socioeconomic differences in accessibility. Future studies might explore constraints impeding accessibility to investigate their contributions in producing the socioeconomic differences in essential travel. Researchers might also extend this research by designing multimodal transportation network models to connect the origins of essential travelers and their frequently visited destinations through appropriate mobility options.

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Appendix.

D-statistics estimated from two-sided Kolmogorov–Smirnov test

	Pre-lockdown vs. lockdown			Pre-lockdown phase			Lockdown phase		
	High SES	Moderate SES	Low SES	High vs. low SES	High vs. moderate SES	Moderate vs. low SES	High vs. low SES	High vs. moderate SES	Moderate vs. low SES
Distance decay effect									
Travel time	0.343	0.292	0.352	0.377	0.062	0.317	0.473	0.120	0.359
Effect of attractiveness factor									
Professional services	0.008 (*ns*)	0.036	0.017	0.057	0.018	0.044	0.058	0.047	0.066
Service jobs	0.043	0.032	0.043	0.140	0.028	0.130	0.103	0.026	0.102
Rental and leasing	0.021	0.033	0.044	0.083	0.042	0.057	0.136	0.082	0.062
Accommodation and food	0.061	0.041	0.067	0.054	0.040	0.039	0.042	0.062	0.045
Recreational facilities	0.071	0.063	0.027	0.184	0.049	0.135	0.142	0.040	0.101
Health care	0.042	0.043	0.072	0.075	0.035	0.051	0.081	0.048	0.065
Education	0.126	0.114	0.109	0.062	0.030	0.046	0.055	0.026	0.034
Retail	0.112	0.099	0.111	0.063	0.014	0.067	0.041	0.054	0.059
Finance	0.061	0.048	0.093	0.091	0.111	0.035	0.070	0.116	0.070

Note: The Kolmogorov D-statistics are all significant at 95 percent confidence level, except for the attractiveness factor of professional services between pre-lockdown and lockdown phase for high SES. *ns* = nonsignificant. SES = socioeconomic status.