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COVID-19 exacerbates unequal food access

Armita Kar [a], Yasuyuki Motoyama [b], Andre L. Carrel [b,c], Harvey J. Miller [a,d], Huyen T.K. Le [a,*]

[a] Department of Geography, The Ohio State University, Columbus, OH 43210, USA
[b] Knowlton School of Architecture, City and Regional Planning Section, The Ohio State University, Columbus, OH 43210, USA
[c] Department of Civil, Environmental and Geodetic Engineering, The Ohio State University, Columbus, OH 43210, USA
[d] Center for Urban and Regional Analysis, The Ohio State University, Columbus, OH 43210, USA

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ABSTRACT

Inequality to food access has always been a serious problem, yet it became even more critical during the COVID-19 pandemic, which exacerbated social inequality and reshaped essential travel. This study provides a holistic view of spatio-temporal changes in food access based on observed travel data for all grocery shopping trips in Columbus, Ohio, during and after the state-wide stay-at-home period. We estimated the decline and recovery patterns of store visits during the pandemic to identify the key socio-economic and built environment determinants of food shopping patterns. The results show a disparity: during the lockdown, store visits to dollar stores declined the least, while visits to big-box stores declined the most and recovered the fastest. Visits to stores in low-income areas experienced smaller changes even during the lockdown period. A higher percentage of low-income customers was associated with lower store visits during the lockdown period. Furthermore, stores with a higher percentage of white customers declined the least and recovered faster during the reopening phase. Our study improves the understanding of the impact of the COVID-19 crisis on food access disparities and business performance. It highlights the role of COVID-19 and similar disruptions on exposing underlying social problems in the US.

1. Introduction

Grocery stores are a key destination in everyday travel. Access to healthy and fresh foods is tied to community health outcomes; ideally, all residents in a city should have access to grocery stores within reasonable travel distance and time. However, the disparity in food access is closely connected to systematic segregation and redlining, both for consumers and retailers (Bower et al., 2014; Reich, 2016; Shannon, 2020; Vargas, 2021). Food stores typically determine their store locations by targeting customers from specific socio-economic groups. For example, the number of dollar stores, mostly SNAP authorized, expanded by 62% in the United States over the last decades, mainly targeting the economically disadvantaged and racially diverse areas (Shannon, 2020).

Consequently, the distribution of supermarkets and grocery stores largely varies by the pre-existing socio-economically segregated pattern of US neighborhoods. Low-income and racially diverse neighborhoods are often served only by low-priced discount stores with affordable but less healthy food products and lack supermarkets and grocery chains with healthier foods. This situation has given rise to a large body of literature measuring the impacts of this uneven distribution of grocery shopping opportunities, often framed around the concept of food deserts (Walker et al., 2010). According to this line of research, residents of food deserts have no choice other than to consume unhealthier food or to travel long distances to access supermarkets that carry a larger or healthier variety of foods.

Underserved communities also often experience disparities in transportation due to transportation services being inadequate or unaffordable (Farber et al., 2016; Lucas, 2019) as a result of a long history of land use and zoning policies that prioritize automobile travel and single-family housing in suburbs. This further exacerbates the problem for households with limited food and transportation budgets and results in very different travel patterns of underserved populations. Thus, recent research has measured food access as a function of both the distance to food stores from residential areas and individual travel patterns and activity spaces (Li & Kim, 2020; Shannon, 2016; Widener et al., 2013). However, most studies measured food access at a single time point in time; only a handful of studies have considered longitudinal changes in food access and food shopping travel. This has resulted in a limited body of research that captures the impact of temporal variations

* Corresponding author. 154 N Oval Mall, Columbus, OH 43210, USA.
E-mail address: le.253@osu.edu (H.T.K. Le).

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in transportation service availability, transit schedules, lifestyle, or similar.

The COVID-19 pandemic disrupted food shopping patterns in an unprecedented way and exacerbated existing problems with food deserts and transportation access. Not only did it cause profound economic hardships to disadvantaged populations and businesses, it also altered work and general travel patterns through limited out-of-home activities and substantial decreases in transit service supply. However, it is not well understood how the impacts differed across population segments, neighborhoods, and types of grocery stores. In light of the abruptness of the shifts brought about by COVID-19, it is critical to investigate the impacts on food access using data with a fine temporal resolution to capture changes in mobility patterns.

The purpose of this study is to assess and investigate changes in travel to supermarkets and grocery stores due to the COVID-19 pandemic. We pursue three objectives: *first*, to quantify the impact of the pandemic on visits to different types of grocery stores throughout several phases of the pandemic; *second*, to investigate spatio-temporal changes in origin-destination travel patterns by different demographics; and *third*, to examine the influence of broader socio-economic and built environment factors on these changes by store type to account for price and customer segments.

Our paper contributes to understanding food shopping access and travel patterns, especially during a disruptive time such as the COVID-19 pandemic. Our work is among the few studies in the food access domain that apply observed data on travel and food shopping behavior with fine temporal resolutions. Additionally, by using an aggregate, city-wide large sample of travel data, this study adds to a holistic understanding of food shopping travel and complements past studies that used observed individual travel data. In addition, our paper distinguishes types of stores based on scale (i.e., local vs. large merchandise stores, general vs. specialized stores) and price, accounting for market segmentation, and further shedding light on food access issues faced by low-income and racially diverse populations. Finally, the COVID-19 pandemic has revealed stresses, weaknesses, and social inequities in many of our social and economic systems; analysis of its impacts on food shopping travel for staple foods can help illuminate these in our food systems.

2. Literature review

2.1. Food deserts and social inequality

A large number of studies concerning groceries and healthy food access have focused on either retail store locations or food deserts (Jiao et al., 2012; Shaw, 2006; Widener et al., 2011; Zenk et al., 2005), which the United States Department of Agriculture (USDA) defines as “low-income census tracts with a substantial number or share of residents with low levels of access to retail outlets selling healthy and affordable foods” (USDA, 2019).

Past studies consistently found that inner cities with higher rates of poverty, unemployment, and vacant units tend to be food deserts (Dutko et al., 2012; Giang et al., 2008; Guy et al., 2004; Semple & Giguere, 2018). This happens largely because of the locations of grocery stores: larger supermarkets with a variety of food options tend to locate in suburban and wealthier areas, while smaller stores dominate in inner cities with low-income population (Chung & Myers, 1999; Moore & Diez Roux, 2006; Zenk et al., 2005). In addition, grocery stores tend to avoid the clusters of fast-food establishments and restaurants that are located in inner cities, further exacerbating the food desert issue (Leslie et al., 2012). As a result, minority neighborhoods in inner cities are often served with independent and small grocery stores, discount stores, and regional supermarkets to fill the gap by large chains (Doussard, 2013; LeDoux & Vojnovic, 2013; Raja et al., 2008).

Nonetheless, reduced access to healthy foods for the low-income population is exacerbated by higher prices for food items charged by smaller stores (Johnson et al., 1996). Shannon (2020) maintained that retail redlining, the discriminatory practice that avoids locating grocery stores in disadvantaged neighborhoods, further pushed low-income and racially diverse populations to rely on low-price retailers (e.g., dollar stores) for food shopping. These locational patterns are associated with income level, race, and ethnicity. For instance, affluent black neighborhoods in Atlanta have lower access to food stores than white counterparts at the same income level (Helling & Sawicki, 2003).

2.2. The built environment and travel patterns for food shopping

The assumption underlying the aforementioned studies is that people purchase food from nearby areas. Hence, areas of residence, such as census tracts or block groups, without healthy and affordable food options are considered disadvantaged. An alternative approach may consider the travel distance from store locations, such as 500m (or 1/3 of a mile) as the distance beyond which people will not walk (Wrigley et al., 2004).

However, people’s grocery travel patterns are not necessarily constrained by simple geographic units or boundaries of their residential areas, distance, or estimated travel time. Many people travel for food outside of their immediate neighborhoods, even when nearer grocers were available (Shannon & Christian, 2017; Zenk et al., 2011). These findings are in line with results by Li and Kim (2020), who argued that individual-level activity spaces were more relevant to food accessibility than the residential neighborhood. Therefore, using observed mobility data is critical for the analysis of food access to capture true travel patterns and look beyond the neighborhood level (Chen & Kwan, 2015; Christian, 2012; Shannon, 2016; Widener et al., 2013). Accessibility to multimodal transportation is another key determinant of travel for food shopping. Past literature demonstrated the differences in grocery travel and accessibility to supermarkets considering the availability of multimodal transportation modes (e.g., automobiles, transit, and walking) and its temporal variabilities (Farber et al., 2014; Widener et al., 2015, 2017). Even low-income residents with transportation disadvantages employ alternate travel strategies, including bus, carpool, or including food shopping as a part of trip chaining (Hallett & McDermott, 2011; Shannon, 2016; Ver Ploeg et al., 2015). Furthermore, recipients of food assistance programs, who are by definition low-income, traveled to stores that were approximately twice as far as the nearest major supermarket (LeDoux & Vojnovic, 2013; Ver Ploeg et al., 2015).

Lastly, attributes of the built environment and an array of travelers’ characteristics have been found to be significant factors in food access (Ewing & Cervero, 2001). Accessibility to destinations, including shops, can be affected not only by locational attributes (e.g., store location, the road network, availability of other activities, property prices) and store attributes (e.g., store size and number of employees), but also by characteristics of travelers (e.g., personal preferences for travel, mode choices, physical and financial constraints) (Helbich et al., 2017; Miller, 2018). Widener et al. (2013) and Shannon and Christian (2017) suggested that trips for food shopping are commonly chained with work trips, making it necessary to consider food retail locations in proximity to jobs.

2.3. Limitations and emerging challenges in studying the impacts of COVID-19

While existing studies have provided some understanding of food accessibility and inequity, the absence of a temporal dimension and observed travel patterns is a major limitation when attempting to apply their findings to estimate the impacts of the COVID-19 pandemic. Specifically, most past studies focused on static analyses instead of changes in accessibility experienced by communities or people over time due to events such as store closures and neighborhood changes. The few studies that considered temporal changes were primarily regional analyses of store closures or changes over a long period. Guy et al. (2004) found that higher-income areas generally got more stores and choices, while lower-income areas faced store closures in Cardiff, UK, from 1989 to 2001. In a case study of Ypsilanti, Michigan, Semple and Giguere (2018) found that areas designated as 'food deserts' shifted over the course of 40 years from predominantly African American neighborhoods to both African American and low-income white neighborhoods. Perhaps the most insightful study was conducted by Shannon et al. (2018), who investigated changes in consumers' shopping behavior relative to the locations of stores accepting food assistance programs during the Great Recession from 2008 to 2012.

A few recent studies investigated the impact of COVID-19 at a high level, i.e., by examining the general decline in business activity. However, they fell short of analyzing how the pandemic and changes in grocery travel patterns may be related to neighborhood or other socio-economic factors. Bartik et al. (2020) suggested that the economic impacts of COVID-19 varied by the scale of business, and small businesses were generally more affected. YelpInc (2020) suggested similar findings from analyzing store closures by store types only at the metropolitan level (e.g., type of restaurants and cuisines). The US Census Bureau (2021) has been conducting a weekly data collection effort, namely the Household Pulse Survey, regarding the level of food sufficiency in the previous seven days during this pandemic at the state level and large metropolitan areas. However, these studies do not inform accessibility and travel patterns at the intra-city level.

In summary, a range of research has advanced the understanding of food accessibility, retail locations, travel behavior, and social inequity. Yet, it has also shown that it is critical to include observed travel behavior when studying food access and go beyond the simple food desert measure based on preidentified geographic units, such as Census tracts, or assumed travel distances. Moreover, temporal changes in food shopping travel patterns need to be considered using individual-level travel data, coupled with the built environment and socio-economic characteristics of neighborhoods. This will help address the current lack of knowledge about the impact of an economic shock on individual-level access to grocery shopping over time.

3. Methods

3.1. Study area and data

Our study area is Franklin County, Ohio, within which the majority of the Columbus, Ohio metropolitan area is located. With a population of 1.3 million (US Census Bureau, 2019b), this area has a community and economic activities that are more diverse than most other areas in Ohio. We used four types of data in this study: (1) store locations and characteristics, (2) store visits, (3) characteristics of incoming travelers as inferred from their origins, and (4) local characteristics of store locations (at the census block group level).

The focus of this study was to understand access to supermarkets and grocery stores that people primarily use for buying staple foods. The selection of stores was mainly based on identifying businesses with NAICS code 445110 that represents supermarkets and other grocery stores and excludes convenience stores, and this sub-sector shares 95 percent of NAICS 4451 grocery stores, according to County Business Patterns 2019 (US Census Bureau, 2019a). We further included large merchandise stores that sell groceries, namely, Walmart, Sam's Club, Costco, and Target. We enriched this store dataset using geographic locations of point-of-interest data from SafeGraph. Among the 438 stores in Franklin County, we successfully matched and retained 393 stores (90%) for this analysis. We also performed a manual inspection of the dataset to ensure that our dataset includes all major local grocery stores in Columbus.

We categorized stores using the USDA classification as an outline, which includes warehouse stores, supercenters, supermarkets, chain stores, and other types (Cho & Volpe, 2017, p. 32) and considering approaches from past research (Leslie et al., 2012; Shannon, 2020; Shannon et al., 2018). We categorized grocery stores into four types: *big-box grocery stores, mid/high-end grocery stores, dollar stores,* and *local stores* based on their retailer brands, NAICS categorization, and store characteristics (employee size and sales volume). *Big-box grocery stores* are warehouse stores and supercenters that sell grocery products (selected from NAICS 452311), including Walmart, Sam's Club, and Costco. *Mid/high-end grocery stores* include supermarkets (selected from NAICS 445110) that are regional brands (retailer franchises expanded in multiple US states) with a larger employee size (25 or more) and sales volume ($5million or more), including Kroger, Target, Trader Joe's, Whole Foods Market, Giant Eagle, and Meijer.

The third category, *dollar stores*, is designated as a single category of chain stores, including all stores of respective discount chains, namely Dollar General, Family Dollar, and Dollar Tree, as well as some independent discount stores (selected from NAICS code 452319). Although often considered a combined category of convenience stores, gas stations, and pharmacies in past research (Shannon et al., 2016, 2018), dollar stores sell staple foods such as grains, meat, fruits, vegetables, and dairy products. Thus they may replace supermarkets in socially disadvantaged neighborhoods (Kelloway, 2018; Shannon, 2020). We did not consider non-traditional food stores such as convenience stores as people prefer to visit supermarkets over these stores for buying staple foods. Especially in Columbus, around 87% (65 out of 75) of the convenience stores (NAICS code 445120) are located within gas stations that are less likely to serve the purpose of primary grocery shops.

Finally, we categorized the local supermarkets, independent grocery stores, limited assortment supermarkets, superettes, and specialty food stores as *local stores*. Similar to mid/high-end grocery stores, this category also contains stores from NAICS code 445110 (Supermarkets and Other Grocery Stores). Unlike the mid/high-end grocery stores category, these stores tend to be smaller and operate within the region. Specifically, 85% of them have the employee size of less than 25 and sales volume of less than $5 million, which are below the thresholds used for mid/high-end groceries. A few local supermarkets are also included in this category as they are local to Columbus and have not expanded their business into any other regions. This category comprises small-scale, local grocery stores, local farmer's markets, meat shops, fish markets, and international grocery stores. In summary, our dataset includes 15 big-box stores, 88 mid/high-end grocery stores, 104 dollar stores, and 186 local stores. We provided the detailed store selection criteria in the Appendix (Table A1).

We obtained data on characteristics of each store (e.g., employee size, sales volumes) from InfoGroup, 2019 dataset (InfoGroup, 2019). This dataset categorizes both big-box and mid/high-end stores based on the type of retail products (e.g., supermarket, gasoline stations, health care and vision, coffee shops). We only used the supermarket/supercenter section of the InfoGroup dataset to ensure that these stores sell grocery products. Fig. 1 illustrates the spatial distribution of different store types in Franklin County. Big-box stores are generally located in suburban areas, with a major concentration of such stores in western and northeastern Columbus. Although mid/high-end grocery stores seem to have a balanced distribution across Columbus, underserved areas located in the central, eastern, and southeastern Columbus do not have any nearby big-box or mid/high-end grocery stores that residents can easily access (Colombo et al., 2012). However, a large concentration of dollar stores and local stores can be found in these neighborhoods. Apart from these neighborhoods, the majority of remaining dollar stores and local stores are found to be clustered in relatively low-income areas (Colombo et al., 2012).

We obtained weekly visitor counts at each store from SafeGraph (SafeGraph, 2020) for the time period from January 06 to June 01, 2020 and enriched the data with travelers' origin and destination data from Streetlight (StreetLight Data, Inc., 2020). Streetlight uses mobile-phone-based locations and timestamps to gather trip information and aggregates origin-destination (OD) flow data using user-defined geographic boundaries. The origins are defined as the geographic area

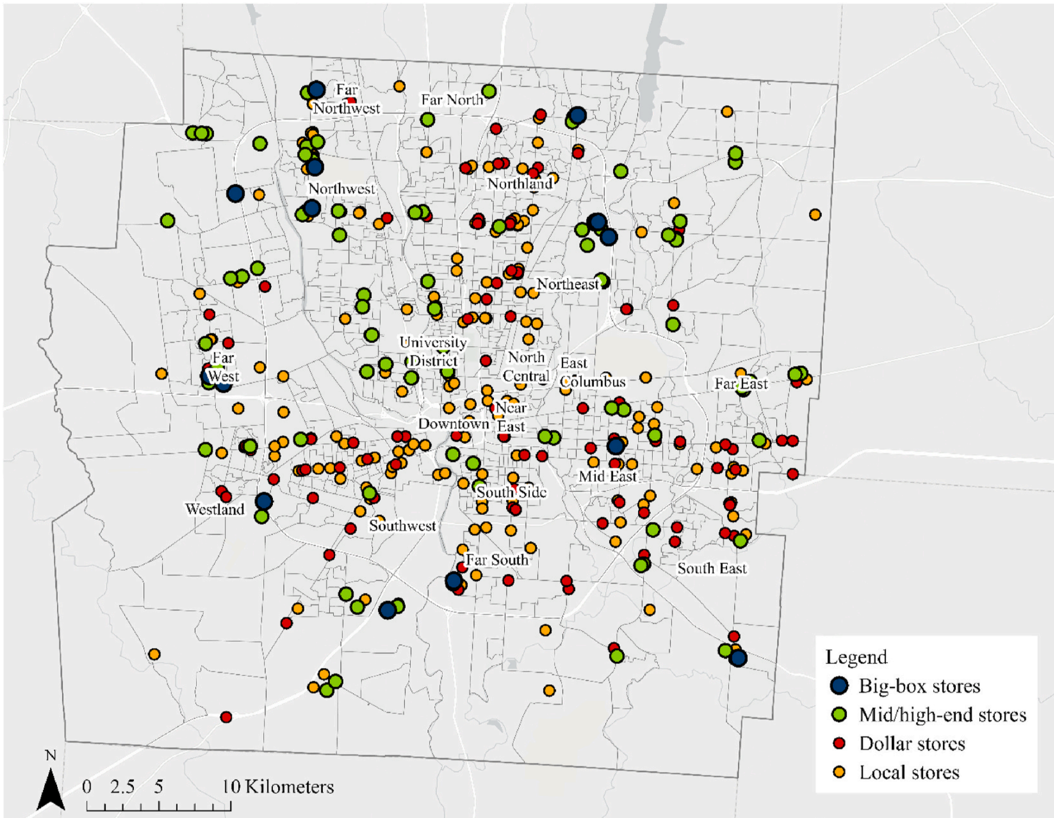

Fig. 1. Spatial distribution of grocery stores in Franklin County, Ohio, categorized by store type.

Table 1
List of explanatory variables.

Variable name	Description	Level of measurement	Unit	Data source	Reference
Store characteristics					
Number of employees	As estimated by InfoGroup	Store	Count	Infogroup	Bartik et al. (2020) and Miller (2018)
Sales volume	As estimated by InfoGroup	Store	Thousands of dollars per year	Infogroup	Bartik et al. (2020)
Travelers' characteristics					
Average trip length	Weighted average trip duration of OD flows to the store parcel	Parcel	Minutes	StreetLight	Ewing and Cervero (2001) and Miller (2018)
Percentage household income less than $50k	Mean percentage of travelers with a household income of less than $50k across the OD flows to the store parcel	Parcel	Percentage	StreetLight	Hallett and McDermott (2011) and Widener et al. (2015)
Percentage of white travelers	Mean percentage of white travelers across the OD flows to the store parcel	Parcel	Percentage	StreetLight	Moore & Diez Roux (2006)
Local characteristics of store locations					
Population density	Total population per square mile	Census block group	Number per square mile	American Community Survey	Ewing and Cervero (2001)
Area type	Categorized by activity density (total number of jobs and dwellings per acre): - Rural: activity density ≤ 0.5 - Suburban: activity density > 0.5 and < 6 - Urban: activity density ≥ 6	Census block group	Category	Smart Location Database	Ewing and Cervero (2001) and Widener et al. (2015)
Job density	Total number of jobs per acre	Census block group	Number per acre	Smart Location Database	Miller (2018) and Widener et al. (2013)
Road density	Miles of road network per square mile	Census block group	Miles per square mile	Smart Location Database	Hallett and McDermott (2011) and Miller (2018)
Multimodal road density	Miles of road network with multimodal facilities per square mile	Census block group	Miles per square mile	Smart Location Database	Farber et al. (2014) and Widener et al. (2015)
Intersection density	Multimodal intersections with four or more road segments per square mile	Census block group	Number per square mile	Smart Location Database	Miller (2018)
Low wage workers	Percentage of low wage workers within a census block group	Census block group	Percentage	Smart Location Database	Miller (2018)

from which the device users started moving, and the destinations represent the geographic area where the device remains still for a certain period of time. In this study, we used the parcels of store locations as destinations and census block groups as origins. Although the origins could be home, work, or any locations, there is a high chance that most travelers performed home-based grocery shopping trips during the COVID-19 pandemic due to the restrictions on non-essential travel and more work-from-home opportunities, especially for well-off communities.

The OD flow data indicate the volumes and origins of visitors from a particular census block group (O) to the parcels where the stores are located (D). Travelers' income, race, and travel time are available for each OD pair. We estimated the average travel time to stores as the weighted average of the travel times of OD flows reaching that store using the following equation:

$$\textit{Weighted average travel time to store } D = \frac{\sum_{i=1}^{n} t_{O_iD} * V_{O_iD}}{\sum_{i=1}^{n} V_{O_iD}}$$

where, t_{O_iD} = average travel time from origin i to the destination of interest

V_{O_iD} = traffic volume from origin i to the destination of interest.

We obtained data at the census block group level, such as population density, from the 2014–2018 American Community Survey 5-year estimates (US Census Bureau, 2020), and built environment characteristics from the Smart Location Database (Ramsey & Bell, 2014). Table 1 provides an overview of the explanatory variables used for this study.

We determined three study periods based on the observed travel patterns manifested in the data. Although the state-wide stay-at-home order was effective from March 22, 2020, our data show a decline in store visits starting from March 16. This early decline in food shopping travel may have been driven by the perception of risk, which is shaped by news and media in addition to the announcement of regulations such as the stay-at-home order. In early March 2020, the news focused on new measures such as halting in-person instruction at public universities and K-12 schools as well as upcoming stay-at-home orders implemented by local establishments and the situation in other states and countries. People started panic-buying and stockpiling grocery products, and foot traffic in retail stores declined even before the official lockdown.

Similarly, regardless of the official reopening date for all retail businesses (May 12, 2020), our dataset showed that the lockdown effect started to dissipate after April 20, 2020, with visitor numbers to stores starting to increase. Therefore, we chose the date ranges that reflect changes in observed travel patterns rather than the presence of official orders. We defined three phases between January 06 to May 31, 2020: (1) the *pre-lockdown* phase between January 06, 2020 and March 15, 2020, (2) the *lockdown* phase between March 16, 2020 and April 19, 2020, and (3) the *initial reopening* phase between April 20, 2020 and May 31, 2020. It is worth noting that we labeled these three phases based on the store visit patterns exhibited in our data (Section 4.1).

3.2. Exploratory analysis: spatial and temporal changes in visitors and OD flows to food stores

We performed a set of exploratory analyses to demonstrate the changes in the study area across time and space. First, we analyzed temporal changes in store visitor numbers for each store type, both in absolute and relative terms. The absolute changes represent the weekly average number of store visitors by store type. The relative changes represent the percentage of changes in the weekly average of store visitors relative to the first week of the study period (January 06 – January 12) by store type.

Second, we visualized the spatial changes in the weekly numbers of visitors to stores. For each of the three phases, we calculated the average weekly visitors to each store. Then, we mapped the changes between the pre-lockdown and the lockdown phase, and between the pre-lockdown and the reopening phase. Changes are represented with proportional symbols, calculated relative to the highest and lowest value of the dataset. We also performed an OD flow analysis to identify changes in the distribution of origins of incoming traffic to store locations. For each OD pair, our analysis considered the average daily traffic originating *from* the origin block groups and destined *to* the parcels associated with the stores.

3.3. Modeling temporal changes in store visits at store locations

Our variable of interest was the difference in average weekly store visits to each store between (1) the pre-lockdown and lockdown phases and (2) between the pre-lockdown and initial reopening phases. Many of the stores in our sample experienced decreases in store visits, but a small number of stores experienced increases. We excluded four stores that had no changes in store visits during this period and averaged zero or one visitors per week, which may be due to measurement errors. For the rest of the stores, we set positive values of changes to 0 and assigned the absolute values for negative changes in traffic.

A hurdle model is a suitable statistical method for count data where the zero and non-zero values are generated by two different processes (Cameron & Trivedi, 2013). A binary logit model captures the first process that generates zero counts, when a threshold (hurdle) is not passed. A truncated negative binomial model captures the second process that generates positive counts when the hurdle is passed. In this study, we estimated two hurdle models to quantify the changes in store visits to determine influential factors affecting the changes. The first model quantifies the effects of COVID-19 during the initial lockdown period, and the second model quantifies the eventual recovery of store visits, immediately before and after statewide restrictions were lifted. Each hurdle model includes (1) a binary logit submodel that determines the probability that a store had a decline in store visits, and (2) a truncated negative binomial submodel that estimates the magnitude of traffic change, given that a store had a decrease in store visits.

We controlled for various independent variables in the hurdle models, including store characteristics, visitors' socio-economics, and characteristics of the store location as guided by relevant studies (Table 1). We included the various categories of store types to account for their different levels of traffic, store characteristics, and most importantly, to understand how low-income and racially diverse populations changed their travel behavior during this disruption.

4. Results

4.1. Summary of temporal changes in store traffic

Fig. 2 illustrates the absolute and relative changes in average weekly traffic by store type for the study period. The average weekly traffic started to decline in the week beginning on March 16 and continued to decline until the week of April 13 (lockdown phase). Average weekly visitors started to increase from the week of April 20 onward (reopening phase). The average changes in store visits during the lockdown period were dominated by changes in big-box store visits and mid/high-end grocery store visits (Fig. 2a).

The visitor data for each store type are normalized to the number of visitors in the week of January 6. It shows that relatively speaking, the declining trend of store visitors for all store types has the same pattern during the lockdown phase (Fig. 2b). However, the growth of visitors beginning in the week of April 20 is higher for big-box grocery stores than other stores, especially during the time period of April 20 to May 10 (the end of the week of May 4).

Table 2 summarizes the variables used for modeling, categorized by store type. The average employee size and sales volume are the highest for big-box grocery stores and the lowest for dollar stores. Most big-box grocery stores belong to block groups with lower population density (153 people/sq. mi), lower road density (11.9%), and lower percentages

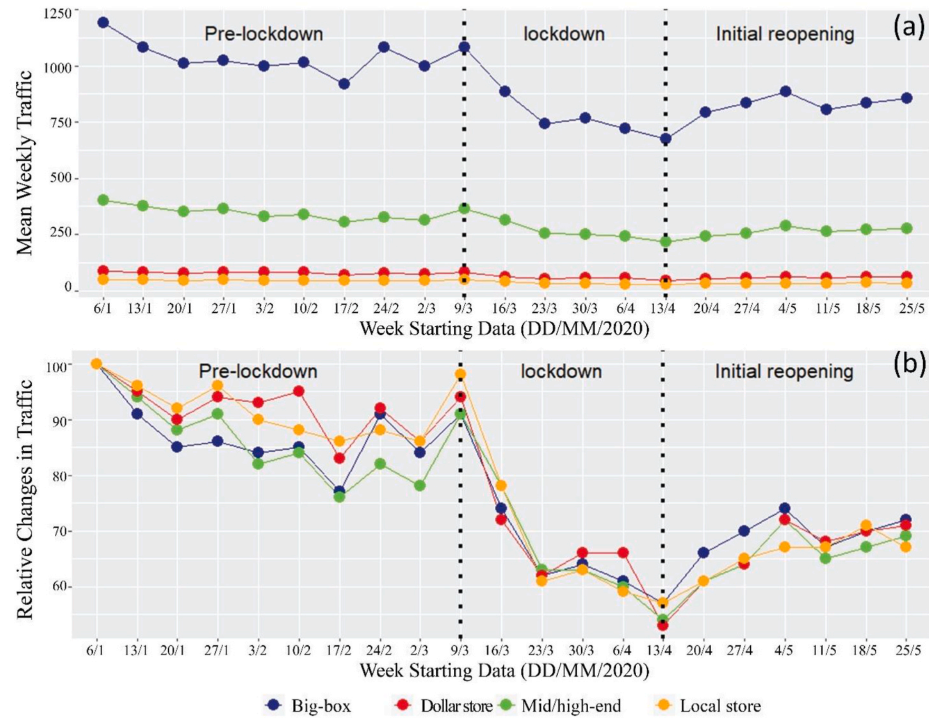

Fig. 2. Absolute changes (a; top) and relative changes (b; bottom) in average weekly store visits, categorized by store types.

Table 2
Descriptive statistics of the variables used in the change analysis.

	Big-box grocery stores		Mid/high-end grocery stores		Dollar stores		Local stores	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Store characteristics								
Employee size	251	*121*	120	*85*	10	*11*	15	*35*
Sales volume	39748	*19178*	26795	*19656*	1319	*706*	6696	*19156*
Local characteristics of store locations								
Number of stores in urban areas	3		45		43		84	
Number of stores in suburban areas	12		42		59		98	
Number of stores in rural areas	0		1		2		4	
Job density	3.40	*3.00*	5.30	*6.58*	3.25	*7.56*	3.80	*6.52*
Percent low-wage workers	39%	*12%*	34%	*13%*	35%	*16%*	33%	*16%*
Road density	11.90	*3.72*	14.43	*6.37*	14.77	*6.26*	15.70	*6.13*
Multimodal road density	2.37	*1.48*	2.91	*1.61*	2.61	*1.66*	2.79	*1.90*
4-way intersection density	2.87	*2.13*	5.70	*7.73*	6.39	*9.39*	8.31	*12.91*
Population density	153	*121*	260	*309*	276	*215*	309	*217*
Average weekly visitors								
Pre-lockdown	1040	*262*	344	*253*	80	*48*	47	*48*
Lockdown	759	*203*	254	*203*	55	*34*	32	*36*
Initial reopening	835	*231*	264	*226*	59	*36*	33	*35*
Change in average weekly visitors								
Lockdown vs. pre-lockdown	−281	*101*	−90	*86*	−25	*24*	−14	*20*
Reopening vs. pre-lockdown	−205	*94*	−80	*79*	−21	*21*	−14	*20*
Average trip length (minutes)								
Pre-lockdown	27	*2*	24	*2*	24	*2*	24	*4*
Lockdown	23	*3*	23	*3*	23	*3*	24	*5*
Initial reopening	24	*3*	23	*4*	23	*4*	23	*4*
Household income less than $50k								
Pre-lockdown	50.8%	*8.0%*	47.6%	*10.4%*	56.4%	*10.6%*	54.2%	*12.7%*
Lockdown	52.6%	*7.3%*	48.8%	*9.7%*	57.6%	*10.4%*	55.1%	*13.8%*
Initial reopening	52.2%	*7.7%*	48.5%	*10.4%*	57.4%	*11.7%*	55.2%	*14.0%*
Percentage of white travelers								
Pre-lockdown	70.3%	*8.9%*	73.7%	*10.3%*	62.9%	*14.0%*	65.8%	*16.5%*
Lockdown	68.1%	*9.3%*	72.2%	*11.0%*	61.7%	*14.0%*	65.6%	*17.0%*
Initial reopening	68.8%	*9.5%*	72.6%	*11.5%*	61.9%	*15.2%*	65.7%	*16.7%*
Percentage of travelers with no high school or high school degree								
Pre-lockdown	43.0%	*9.7%*	38.7%	*10.8%*	49.3%	*10.9%*	45.2%	*12.2%*
Lockdown	43.9%	*9.4%*	39.5%	*10.2%*	49.9%	*10.4%*	46.2%	*13.6%*
Initial reopening	43.0%	*9.9%*	39.3%	*10.5%*	50.1%	*11.4%*	46.6%	*13.5%*

of low-wage workers (39%) than the other types of stores.

During the pre-lockdown phase, the average weekly visitors to big-box, mid/high-end, and dollar stores were 22.1, 7.3, and 1.7 times higher than the average weekly visitors to local stores, respectively. Although on average, all types of stores had a decline in visitors during the lockdown and reopening phases, the big-box grocery stores received 23.7 times and 25.3 times more average weekly visitors than local stores. There was little to no difference in customers' travel time to all three store types: on average, people spent 23–27 min to access grocery stores.

With regard to shoppers' demographics before lockdown, the percentages of low-income travelers (i.e., with annual household incomes below $50,000) are lowest for mid/high-end grocery stores (47.6%) and highest for dollar stores (56.4%). The percentage of white customers was highest at mid/high-end grocery stores (73.7%) and lowest at dollar stores (62.9%). The socio-economic composition of visitors by store type did not drastically change across the three study periods.

4.2. Exploratory analysis of spatial and temporal changes in store visits

Fig. 3 shows the changes in average weekly store visitors between phases. The change from the pre-lockdown phase to the lockdown phase, as reflected in the proportional symbols, is very low for dollar stores and local stores as compared to big-box grocery stores and mid/high-end grocery stores (Fig. 3a). During the reopening phase (Fig. 3b), the proportional change for mid/high-end, dollar, and local stores is greater as compared to the changes in the big-box grocery stores.

Figs. 4–5 illustrate the absolute changes in OD flows to stores between the three phases. Darker lines represent larger declines. Between the pre-lockdown and the lockdown phases, the decline in visits to big-box and mid/high-end grocery stores from nearby origins was higher than that from distant origins (Fig. 4). Although big-box stores had the highest decline during the lockdown phase, they recovered faster than other types of stores, mostly from short-distance visits (Fig. 4b). For mid/high-end grocery stores, the decline in OD flow was more pronounced in the reopening phase from nearby origins and some distant origins, such as the northeastern parts of Columbus (Fig. 4d).

There are distinctive patterns in OD flow changes among the store types. Neighborhoods without supermarkets (i.e., food deserts) had smaller changes in OD flows to dollar stores and local stores during both lockdown and initial reopening phases (Fig. 5). For other neighborhoods, most dollar stores experienced a higher decline in incoming flow during the lockdown phase; some of these declines persisted in the reopening phase (Fig. 5a and b). Similarly, the northwestern part of Columbus (west of downtown and the university district), containing mostly high-income neighborhoods, experienced a major decline in flows to the local stores that are in close proximity to mid/high-end grocery stores (Fig. 5c and d).

4.3. Modeling temporal changes in store visits

Table 3 presents the estimation results of the hurdle models. The binary logit submodel estimates the probability of a store experiencing a decline in traffic during both the lockdown and initial reopening phases. The table reports the coefficient estimates, *p* values, and odds ratio (OR). The model results indicate that the probability that a store located in an urban area experienced a decline in traffic was 7.53 times and 7.28 times more than that of a store located in a rural area during the lockdown and initial reopening phases respectively. Job density around the store (at census block group level) significantly affected traffic changes during COVID-19 ($OR_{lockdown} = 0.94$, $OR_{reopening} = 0.95$, $p < 0.05$). Although the effects of travel time and income were statistically insignificant, we found that stores with higher percentages of white travelers were less likely to have a decline in store visits during the reopening phase ($OR_{reopening} = 0.02$, $p < 0.05$).

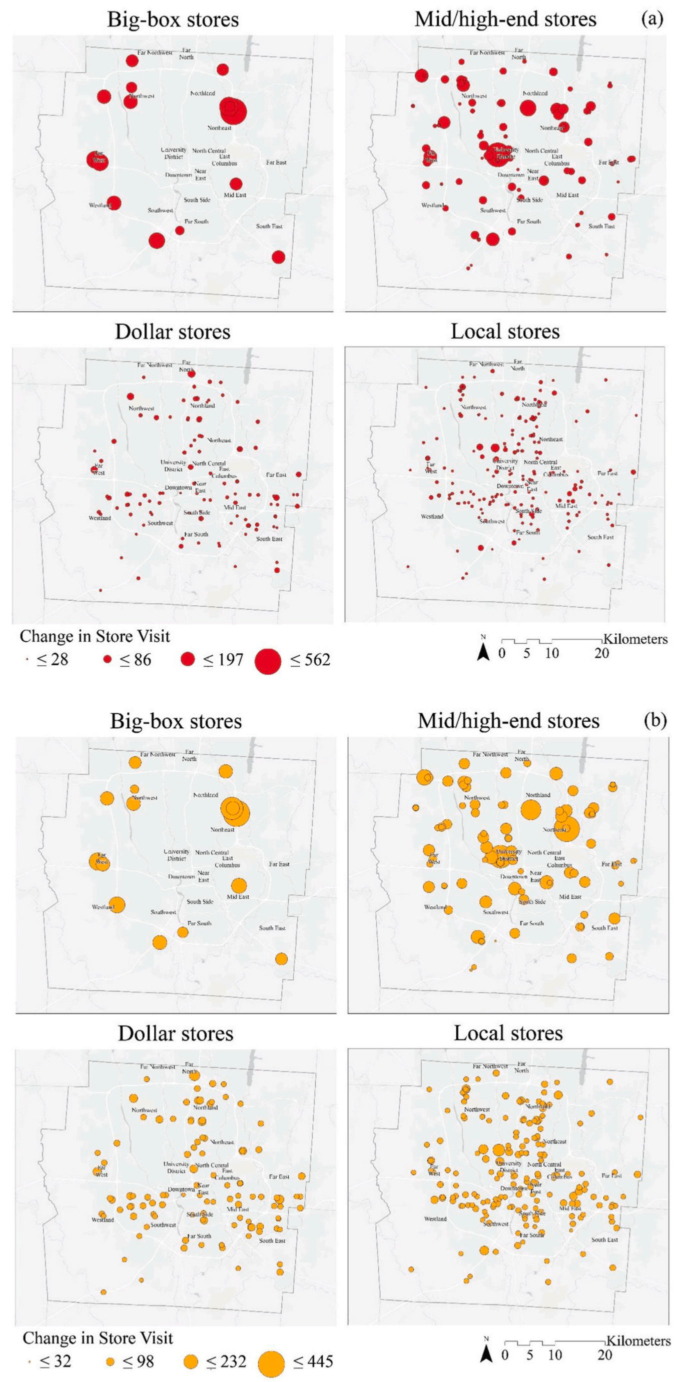

Fig. 3. Changes in average weekly store visitors; a) between pre-lockdown and lockdown phase (top), and b) between pre-lockdown and initial reopening phase (bottom).

The truncated negative binomial submodels account for the magnitude of traffic decline at the stores that experienced a decline during the periods of interest. Table 3 reports the coefficient estimates, p-values, and the incidence rate ratio (IRR). The results indicate that, compared to big-box grocery stores, the average decline in weekly visitors between the pre-lockdown and lockdown phase was 64% (202 visitors) for mid/high-end grocery stores, 87% (73 visitors) for dollar stores, and 92% (49 visitors) for local stores. Model 2 estimates an average decline of 281 weekly store visitors between the pre-lockdown and initial reopening phase, suggesting an overall recovering pattern in grocery stores. However, compared to big-box stores, the average decline in weekly

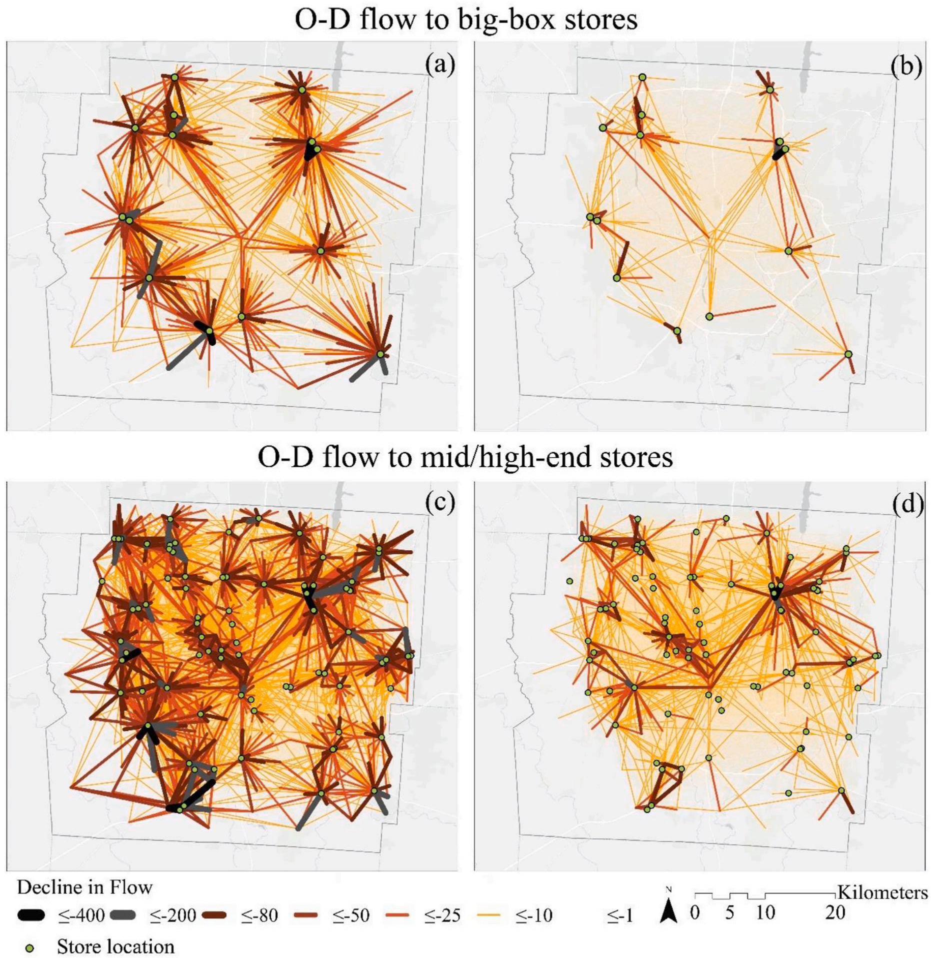

Fig. 4. Changes in OD flows to big-box stores (top panel) and to mid/high-end grocery stores (bottom panel) between pre-lockdown and lockdown phase (a, c) and between pre-lockdown and initial reopening phase (b, d).

visitors was 53% (132 visitors) for mid/high-end grocery stores, 84% (39 visitors) for dollar stores, and 90% (28 visitors) for local stores.

During the lockdown phase, stores located in urban areas experienced a traffic decline 2.5 times higher than those located in rural areas. Also, both the income and racial profiles present a negative association with the magnitude of decline in store visitors. Store visits were likely to decline by a factor of 0.10 with each percentage increase in low-income population ($p < 0.01$) and to decline by a factor of 0.37 with each percentage increase in white travelers ($p < 0.08$). However, neither travelers' characteristics nor local characteristics of stores show statistically significant effects on the decline in store visitors during the reopening phase.

We performed a Moran's I test for spatial autocorrelation using the residuals from the hurdle models. We used bandwidths ranging from 500m–3000m with a 500m interval. For big-box grocery stores, mid/high-end grocery stores, and dollar stores, we found no indication of spatial autocorrelation ($p > 0.05$). This finding indicates that the residuals of both models are not spatially correlated and the observed traffic decline of each store is not influenced by the attributes of nearby stores. For the local stores, our tests indicate the presence of weak spatial autocorrelation with a bandwidth of 2500m (Moran's $I = 0.102$, $p < 0.05$ for the hurdle model between the pre-lockdown and lockdown phase; Moran's $I = 0.126$, $p < 0.05$ for the hurdle model between the pre-lockdown and reopening phase). The null spatial autocorrelation at a bandwidth of 2500m for local stores is plausible, as local and ethnic grocery stores tend to have small building footprints and customer capacity, at the same time they tend to cluster with local stores in certain areas of Columbus. In summary, we find that our hurdle model results do not need to further account for spatial effects between stores.

5. Discussion

Our study investigated spatio-temporal changes in visitor traffic to various types of food stores in Columbus, Ohio, including supermarkets and big-box retailers, before and after the lockdown due to the COVID-19 pandemic. We categorized changes in store visitor numbers throughout three phases that were defined based on observed store visit patterns: the pre-lockdown phase, the lockdown phase, and the initial reopening phase. We observed that at the aggregate level, all types of food retailers experienced a decline in their weekly visitor numbers during the lockdown phase and did not reach their pre-lockdown levels by the end of May 2020. Our major findings are explained in the following paragraphs.

First, we found that the decline and recovery of store visits to grocery stores varied by store type. While the decline during the lockdown was larger for big-box retailers and smaller for dollar stores, the recovery was faster for big-box retailers and slower for mid/high-end grocery stores and other types of stores during the initial reopening phase. This finding is consistent with previous economic studies (Bartik et al., 2020) that the magnitude of the economic impacts of COVID-19 was lower for large businesses than for small businesses.

Second, during the reopening phase, big-box and mid/high-end grocery stores experienced a recovery of visitors from nearby locations but not of visitors who traveled long distances. In contrast, the visitor

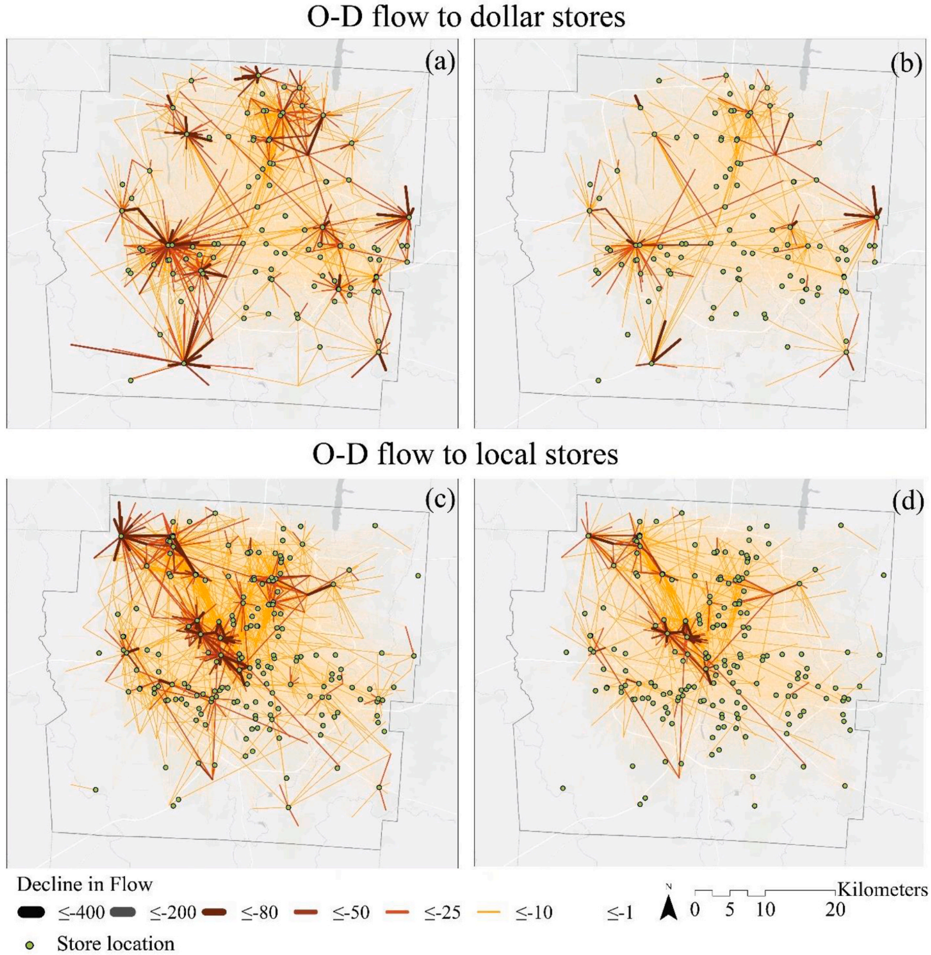

Fig. 5. Changes in OD flows to dollar stores (top panel) and to local stores (bottom panel) between pre-lockdown and lockdown phase (a, c) and between pre-lockdown and initial reopening phase (b, d).

declines for dollar stores and local stores primarily took place in wealthier areas, while store visits in low-income areas had smaller changes, even during the lockdown period. One possibility is that some shoppers stocked up on household commodities from large stores and thus reduced their travel during the lockdown phase. Higher-income households may have been more likely to do so than their lower-income counterparts with access to smaller storage areas and smaller food shopping budgets.

Third, we found a significant difference in customers' socio-economic characteristics by store type and locational attributes. As indicated in the exploratory analysis, big-box and mid/high-end grocery stores received more high-income and white travelers than dollar stores and local stores. Meanwhile, our models indicated that while the percentage of low-income customers and the percentage of white customers were negatively associated with traffic declines during the lockdown, each percent increase in low-income customers had a smaller effect on traffic decline than each percent increase in white customers. Additionally, stores with a higher percentage of white customers were more likely to recover during the reopening phase. The link between store traffic and demographics, that is, dollar stores being dominated by low-income shoppers and big-box and mid/high-end stores being dominated by white and higher-income shoppers, may explain the more substantial decline and faster rebound of big-box and mid/high-end stores.

Our findings that suggest a smaller magnitude of decline in stores visited by low-income and white populations also imply that access to supermarkets and its association with different neighborhood socio-economic characteristics is a major driver of changes in food shopping patterns. Similar to Moore & Diez Roux (2006) and Zenk et al. (2005), low-income neighborhoods in our study area also tended to lack access to nearby supermarkets. These limited choices for low-income neighborhoods led to a situation in which residents of such neighborhoods continued to travel to dollar stores and local stores for their grocery shopping needs. Furthermore, similar to the findings of LeDoux and Vojnovic (2013) and Ver Ploeg et al. (2015), our OD flow analysis confirmed that the majority of long-distance travel to supermarkets in the pre-lockdown phase originated from low-income areas. By and large, residents of such areas reduced long-distance grocery travel and still did not visit farther-away supermarkets during the reopening phase. Previous studies of Hallett and McDermott (2011) and Shannon (2016) emphasized the dependency of low-income people on multimodal travel options for food access, and Widener et al. (2013) and Shannon and Christian (2017) identified the association between food shopping and travel to work. The restrictions during COVID-19, which impacted the availability of multimodal transportation options and shut down many workplaces, may have imposed barriers on both long-distance travel and travel to work, and limited access to larger supermarkets for underserved low-income neighborhoods.

Fourth, we found that the decline of store visitors was associated with locational attributes, namely urban status and job density. The probability of seeing a decline in visitors was higher in urban areas and areas with higher job density. The magnitude of decline was also higher in urban areas during the lockdown phase, but not during the initial reopening phase. In contrast, suburban areas were more likely to see a slower recovery of grocery store visits during the initial reopening

Table 3
Hurdle model results: decline in store visits through the lockdown and reopening phases.

	Model 1: Decline between pre-lockdown and lockdown phases			Model 2: Decline between pre-lockdown and initial reopening phases		
	Binary logit submodel					
	Coef.	***p value***	***OR***	***Coef.***	***p value***	***OR***
Intercept	13.51	0.99	7.4e+05	19.65	0.99	3.4E+08
Store types (ref: big-box grocery stores)						
Mid/high-end grocery stores	−12.55	0.99	0.00	−14.78	0.99	0.00
Dollar stores	−12.59	0.99	0.00	−15.56	0.99	0.00
Local stores	−14.33	0.99	0.00	−16.61	0.99	0.00
Store characteristics						
Employee size	0.01	0.19	1.01	0.00	0.72	1.00
Travelers' characteristics						
Trip duration	0.01	0.82	1.01	−0.01	0.89	0.99
Low income population (%)	3.32	0.28	27.66	0.03	0.99	1.03
White population (%)	−1.35	0.54	0.26	**−4.15****	**0.02**	**0.02**
Local characteristics of store locations						
Suburban area (ref: rural area)	1.57	0.15	4.79	**1.55***	**0.09**	**4.70**
Urban area (ref: rural area)	**2.02***	**0.09**	**7.53**	**1.99****	**0.04**	**7.28**
Population density	0.00	0.89	1.00	0.00	0.69	1.00
Job density	**−0.06****	**0.04**	**0.94**	**−0.05***	**0.07**	**0.95**
Multimodal road density	0.08	0.61	1.08	0.17	0.20	1.19
4-way intersection density	−0.02	0.34	0.98	−0.02	0.26	0.98
Low-income workers (%)	−1.30	0.32	0.27	−1.03	0.36	0.36
	Truncated negative binomial submodel					
	Coef.	***p_value***	***IRR***	***Coef.***	***p_value***	***IRR***
Intercept	**6.33*****	**0.00**	**560.11**	**5.64*****	**0.00**	**281.11**
Store types (ref: big-box grocery stores)						
Mid/high- end grocery stores	**−1.02*****	**0.00**	**0.36**	**−0.77****	**0.01**	**0.47**
Dollar stores	**−2.04*****	**0.00**	**0.13**	**−1.99*****	**0.00**	**0.14**
Local stores	**−2.43*****	**0.00**	**0.09**	**−2.29*****	**0.00**	**0.10**
Store characteristics						
Employee size	0.00	0.24	1.00	0.00	0.51	1.00
Travelers' characteristics						
Trip duration	−0.01	0.77	0.99	−0.00	0.91	0.99
Low-income population (%)	**−2.28*****	**0.01**	**0.10**	−0.97	0.25	0.38
White population (%)	**−1.01***	**0.08**	**0.37**	−0.50	0.39	0.61
Local characteristics of store locations						
Suburban area (ref: rural area)	0.73	0.12	2.08	0.22	0.70	1.24
Urban area (ref: rural area)	**0.92***	**0.06**	**2.51**	0.42	0.46	1.52
Population density	0.00	0.45	1.00	0.00	0.35	1.00
Job density	0.03	0.10	1.03	0.02	0.19	1.02
Multimodal road density	0.00	0.94	1.00	−0.03	0.55	0.98
4-way intersection density	−0.01	0.23	0.99	−0.01	0.11	0.99
Low-income workers (%)	0.49	0.21	1.63	0.49	0.23	1.62
Log(theta)	**0.25***	**0.09**		**0.17***	**0.09**	
Goodness-of-fit statistics						
Log-likelihood			−1615			−1585
AIC			3292			3232

Significance codes: p value < 0.01: '***', p value < 0.05: '**', p value < 0.1: '*'. Model 1: $n_{total} = 393$ stores ($n_{decline\ in\ visitors} = 354$ stores; $n_{increase\ in\ visitors} = 39$ stores). Model 2: n = 393 stores (decline in store visitors: 341 stores, positive or no changes in store visitors 52 stores).

phase, but the magnitude of decline was not statistically different from rural areas. Unlike many studies that relied on distance or travel time as a determinant to identify food deserts, we found travel time to be insignificant in our models. This implies that not only physical distance and thus exposure to nearby food retailers (Widener & Shannon, 2014) plays a role in shaping low-income populations' food shopping travel patterns, but also other social dimensions, such as price and transportation accessibility (Shannon & Christian, 2017; Widener et al., 2013).

The strengths of our study include the use of comprehensive data on observed travel patterns with a large and refined spatio-temporal scale. This allows us to infer shopping travel patterns for the population, thus complementing previous work that relies on a sample of individual travel data measured at one or a few time points (e.g., cross-sectional data or longitudinal data with a small number of waves). Our analysis also emphasizes changes in the travel patterns of multiple population segments, considering customers' income and race, across different store types and store sizes. This provides a holistic view of disparities in food access from both store and household standpoints.

This study has several limitations. First, the OD flow data was limited to parcel sizes, resulting in an underestimation of the area size of big-box and mid/high-end grocery stores, which may occupy more than one parcel, and overestimation of the size of dollar and local stores, which may share the same parcel with other businesses. Second, measurement errors exist, as store visitors may have shopped for non-grocery products. Besides, our study assumes that all stores considered in this study sell a variety of staple foods. However, some stores may carry a more limited collection of staple foods than others (e.g., dollar stores), an aspect that our study could not address. Third, online shopping data were not available in this study. For big-box and mid/high-end grocery stores that offer home delivery options to their customers, the number of store visitors may not reflect the true purchase activity. On a related note, store visits do not equate with the amount of consumption. It is possible that a person's store visits may decrease, but the overall spending may increase. Regarding the sampling and data collection practices, our data may have biases, potentially omitting populations with limited access to cell phones and other forms of communication technology. Additionally, data collection practices were not disclosed to us in detail. Future studies may consider coupling these data sets with other types of data to obtain a more comprehensive view of grocery shopping travel.

6. Conclusions

This study investigates the impacts of the COVID-19 pandemic on travel patterns for grocery shopping in Columbus, Ohio. We estimated and compared changes in store visitor numbers across different store types to detect discrepancies in the impact of the pandemic among different customer segments and among four types of stores, namely mid/high-end grocery stores, big-box grocery stores, dollar stores, and local grocery stores. We found that COVID-19 exposes the existing disparities in food access and travel of underserved population, and that smaller stores, such as local stores and dollar stores experienced a slower recovery in store visits during the initial reopening phase of COVID-19 as compared to the larger store types.

Our findings indicate that residents of low-income neighborhoods and food deserts became further constrained in their access to high-quality food during the pandemic. This highlights the importance of policies to provide or maintain transportation services that allow residents of such neighborhoods to continue accessing healthy food options, or to bring healthier food options to areas with few store choices. Furthermore, our findings show the importance of local and small-scale stores in providing access to food for low-income neighborhoods, which suggests that policies and relief funds to support such stores would benefit marginalized populations.

Our study contributes to enhancing our understanding of how food shopping patterns are driven by socio-economic and built environment characteristics during a major disruption, thus emphasizes the pre-existing structural inequality in the US. Furthermore, it contributes to understanding the resilience of various store types to such a disruption, especially in light of the locational attributes captured by our study. The study can help practitioners and policy makers develop strategies to support the neighborhoods and local businesses that are disproportionately impacted by COVID-19 to recover after the pandemic. Insights from this study can also support preparations for future disruptions and recessions that disproportionately affect smaller businesses and marginalized populations. Lastly, the study demonstrates an analytical framework that can be applied in other cities and contexts.

Author contribution statement

AK: Methodology, Data Curation, Formal analysis, Investigation, Writing - Original draft, Writing - Review & Editing, Visualization. YM: Conceptualization, Methodology, Writing - Original draft, Writing - Review and Editing. ALC: Conceptualization, Methodology, Investigation, Writing - Original draft, Writing - Review and Editing. HJM: Conceptualization, Writing - Review & Editing. HTKL: Conceptualization, Methodology, Investigation, Writing - Original draft, Writing - Review & Editing, Supervision.

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Appendix

Table A1
Summary of store characteristics and categorization criteria

		Big-box stores	Mid/high-end grocery stores	Dollar stores	Local stores
Employee size	**Min**	65	30	4	1
	Max	500	350	30	150
	Median	250	135	7	5
	Mean	251	120	10	15
	S.D.	121	85	11	35
Sales Volume (in thousands)	**Min**	10280	7043	600	54
	Max	79073	79989	1423	67403
	Median	39537	24651	1050	940
	Mean	39748	26795	1319	6696
	S.D.	19178	19656	706	19156
Store types and selection criteria		Warehouse clubs and supercenters that sell groceries	Department stores and regional supermarket chains that sell groceries with an employee size greater than 25 and sales volume greater than 5 million.	Discount stores of dollar chains	Local supermarkets, independent grocery stores, limited assortment supermarkets, superettes, and specialty food stores
NAICS code		452311 (warehouse clubs and supercenters)	452210 (Department stores) and 445110 (Supermarkets and Other Grocery (except Convenience) Stores)	NAICS code 452319 (All other general merchandise stores)	Rest of the stores from 445110 which do not fulfill the criteria of other 3 categories
Example store names		Walmart, Sam's Club, and Costco	Kroger, Target, Trader Joe's, Whole Foods Market, Giant Eagle, and Meijer	Dollar General, Dollar store, Family Dollar, and Dollar Tree	Raisin rack natural food market, The Hills market, Saraga international grocery, Istanbul supermarket, Yasmin international market

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