Impact of COVID-19 on Food Shopping: A Spatio-Temporal Analysis of Changes in Travel to Supermarket and Grocery Stores

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This paper is currently under reviewed.

ABSTRACT

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 lockdown. We examined customers' shopping travel patterns by demographic segments, including low-income populations and racial minorities. By considering four types of food retailers, segmented by price levels and business size, we visualized and estimated the decline and recovery patterns of store visits during the pandemic. We developed two hurdle models to identify the key socio-economic and built environment determinants of the store traffic changes. The results show a clear 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, albeit mostly based on visits from nearby neighborhoods. Visits to stores in low-income areas, and especially in food deserts, experienced smaller changes even during the lockdown period. Percentage of low-income and white customers were negatively associated with the magnitude of traffic decline to a store during the lockdown period. Meanwhile, stores with a higher percentage of white customers recovered faster during the reopening phase. Our study contributes to developing a better understanding of the impact of the COVID-19 crisis on food access disparities and business performance. Quantifying how the pandemic disrupted food shopping travel can illuminate the social dimensions of access to healthy foods and support the development of resilient and equitable food systems, as well as strategies for the economic revival of affordable and healthy food retailers.

Keywords: food desert, shopping travel, COVID-19, equity, economic development

1 INTRODUCTION

Grocery stores are a cornerstone of non-commute 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, in most U.S. cities, access to groceries varies considerably between neighborhoods. Low-income and disadvantaged neighborhoods are often not served by grocery chains that carry such foods, and cheaper discount stores often stock foods that are affordable yet less healthy.

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. 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 carrying a larger or healthier variety of foods. This additional need for travel is problematic for households that have constrained food budgets and transportation options. While food access has typically been measured as the distance from residential areas, it is also a function of individual travel patterns and activity spaces (Li & Kim, 2020; Shannon, 2016; Widener et al., 2013). Additionally, most studies measure food access at a single time point; only a handful of studies have considered longitudinal changes in food access and food shopping travel. This has resulted in a fairly limited body of research that captures the impact of temporal variations in transportation service availability, transit schedules, lifestyle, or similar.

The COVID-19 pandemic is an unprecedented disruption to food shopping patterns and exacerbates existing problems with food deserts. Not only did it cause profound economic hardships to disadvantaged populations and businesses, it also altered work and travel patterns,

including substantial decreases in transit service supply and demand, resulting in considerable effects on marginalized populations' access to groceries. It is not well understood in what way 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 visualize the spatio-temporal changes in traffic flows by 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 the understanding of food shopping access and travel patterns, especially during a disruptive time such as the COVID-19 pandemic. Our study is among the few studies in the food access domain that apply observed travel data and actual food shopping behavior with refined temporal resolutions. Additionally, by using an aggregate, city-wide large sample of travel data, this study complements past studies using observed individual travel data, thus providing a holistic understanding of food shopping travel. Finally, 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 racial minority populations.

2 LITERATURE REVIEW

A large number of studies concerning groceries and healthy food access focus on retail store locations. Earlier studies focused on identifying food deserts (Jiao et al., 2012; Shaw, 2006), 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). These studies assumed that people purchase food from nearby areas; hence, geographic areas of residence, such as census tracts or block groups, without healthy and affordable food options are considered disadvantaged. Other research has expanded the definition of food deserts by incorporating transportation mode and travel time. In general, scholars in food studies considered 500m (or, equivalently, 1/3 of a mile) as the distance beyond which people will not walk (Wrigley et al., 2004). The consideration of the transportation system also allows the examination of temporal patterns: Widener et al. (2017) investigated how grocery travel and accessibility can vary as a function of the time of day. Helbich et al. (2017) analyzed food accessibility from the perspective of both transportation accessibility and property prices.

Food accessibility is not geographically uniform, and the extant research generally agrees that it tends to be lower in areas of poverty, with high unemployment rates, high percentages of vacant homes, and in communities of color (Dubowitz et al., 2008; Dutko et al., 2012; Semple & Giguere, 2018). More pronounced yet complicated disparities emerge if we consider different types of food stores. Minority neighborhoods tend to lack healthful food sources, such as full-scale supermarkets, compared to predominantly white neighborhoods (Moore & Diez Roux, 2006; Zenk et al., 2005). However, the former are not entirely devoid of food access, as

independent and small grocery stores, discount stores, and regional supermarkets may be available (LeDoux & Vojnovic, 2013; Raja et al., 2008). Doussard (2013), for instance, showed that an ample selection of produce and meat was available to low-income Latino communities through independent markets in Chicago.

It became clear that people's grocery travel patterns were not constrained by simple geographic units or boundaries of their residential areas, distance, or estimated travel time. While many food desert studies considered residential-based proximity to food stores as a measure of food exposure, Shannon & Christian (2017) and Zenk et al. (2011) argued that this was a poor proxy for food shopping activities. Using observed travel patterns, they found that most people shopped for food outside of their immediate neighborhoods, even when nearer grocers were available. These findings are in line with results by Li & Kim (2020), who argued that individual-level activity spaces were more relevant to food accessibility than the residential neighborhood. Given the inadequacy of using small geographical boundaries to capture true travel behavior, it is critical to use observed mobility data for the analysis of food access (Chen & Kwan, 2015; Christian, 2012; Shannon, 2016; Widener et al., 2013). This necessitates the use of observed travel patterns and looking beyond the neighborhood level to understand problems with food shopping.

Among many factors that affect travel patterns, built environment attributes and traveler's socio-economic attributes have been found to be key factors (Ewing & Cervero, 2001). Accessibility to destinations, including shops, can be affected not only by locational attributes (e.g., store location, road networks, availability of other activities) and store attributes (e.g., store size and employee size), but also by characteristics of travelers (e.g., personal preferences of travel, mode choices, physical and financial constraints) (Miller, 2018). Widener et al. (2013) and Shannon &

Christian (2017) suggested that food shopping is commonly being chained with work trips, therefore it is necessary to consider food retail locations in proximity to jobs.

Some of the aforementioned factors were reflected in studies on food accessibility. For instance, Farber et al. (2014) and Widener et al. (2015, 2017) integrated the influence of the multimodal transportation network (i.e., a combination of multiple transportation modes, such as automobile, public transit, and walking) and its temporal variations in evaluating accessibility to supermarkets. Hallett & McDermott (2011) and Shannon (2016) found that even low-income residents managed to shop using various transportation modes, including bus, carpool, and driving. 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).

A major limitation of many existing studies is the absence of the temporal dimension, in other words, changes in accessibility experienced by communities or people over time due to events such as store closings and neighborhood change. Among the few studies that considered temporal changes, Guy et al. (2004) examined store closures and openings in Cardiff, UK, from 1989 to 2001, with higher-income areas generally getting more stores and choices, while lower-income areas faced store closures. In a case study of Ypsilanti, Michigan, Semple & 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.

Some studies have focused on store types when analyzing food accessibility (Shannon, 2016, 2020). Shannon (2020) maintained that retail redlining, the discriminatory practice that avoids locating grocery stores in disadvantaged neighborhoods, further pushed low-income and racial minority populations to rely on low-price retailers (e.g., dollar stores) for food shopping. Separately, Bartik et al. (2020) suggested that the economic impacts of COVID-19 varied by the scale of business. Therefore, studies in food shopping should consider multiple categories of the food stores and scale (e.g., the number of employees) for a better understanding of food shopping for multiple population segments and how this impacts businesses.

3 METHODS

3.1. Study area and data

Our study area is Franklin County, Ohio, in which the majority of the Columbus, Ohio metropolitan area is located. With a population of 1.3 million people (US Census Bureau, 2019), 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 business-specific information, (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).

As this study focused on access to grocery shopping opportunities, we included supermarkets and other grocery stores and excluded convenience stores. The selection of stores was primarily based on identifying businesses with NAICS code 445110, but we further included large merchandise stores that sell groceries, namely, Walmart, Sam's Club, Costco, and Target. We enriched this dataset with point-of-interest data from SafeGraph. Among the 438 stores in Franklin County, we successfully matched and retained 393 stores (90%) for this analysis.

As suggested by Leslie et al. (2012), Shannon (2020), and Shannon et al. (2018), we categorized grocery stores into four types: *big-box grocery stores*, *mid/high-end grocery stores*, *dollar stores*, and *other stores*. The category of big-box grocery stores includes large merchandise stores, namely Walmart, Sam's Club, and Costco. The mid/high-end grocery stores include Kroger, Target, Trader Joe's, Whole Foods Market, Giant Eagle, and Meijer. The third category, dollar stores, includes all stores of respective discount chains, namely Dollar General, Family Dollar, and Dollar Tree, as well as some independent discount stores. We categorized the remaining stores with NAICS code 445110 that did not fall into one of these three categories as *other stores*, which include small-scale, local grocery stores, local farmer's markets, meat shops, fish markets, and international grocery stores. Our dataset consists of 15 big-box stores, 88 mid/high-end grocery stores, 104 dollar stores, and 186 *other stores*.

Figure 1 illustrates the spatial distribution of the different store types in Franklin County. Big-box stores are generally located in suburban areas, with a major concentration of such stores in the western and northeastern parts of the Columbus urban area. Although mid/high-end grocery stores seem to have a balanced distribution across Columbus, the underserved areas located in the central, eastern, and southeastern parts of 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 stores categorized as "*other stores*" can be found in these neighborhoods. Apart from these neighborhoods, the majority of other dollar stores and local stores are found to be clustered in relatively low-income areas (Colombo et al., 2012). The varying spatial distributions of these store types and association with local socio-economic characteristics further justifies our categorization of stores.

Figure 1: Spatial distribution of grocery stores in Franklin County, Ohio, categorized by store type

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), using the size of the parcels of store locations as a proxy for store size. The origin-destination (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.

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), built environment characteristics from the Smart Location Database (Ramsey & Bell, 2014), and business-specific information (e.g., employee size, sales volumes) from InfoGroup data collected in 2019 (InfoGroup, 2019). Table 1 provides an overview of the explanatory variables used for this study.

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-specific	Count	Infogroup	Bartik et al. (2020) and Miller (2018)
Sales volume	As estimated by InfoGroup	Store-specific	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 & 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 & 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 & 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 & 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)

Variable Name	Description	Level of measurement	Unit	Data Source	Reference
Road density	Miles of road network per square mile	Census block group	Miles per square mile	Smart Location Database	Hallett & 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)

The Ohio Department of Health issued a stay-at-home order on March 22, 2020. However, a decline in store visits is evident beginning in the week of March 15, 2020 (coinciding with the spring break of a large Columbus-based public university and cancellation of all in-person classes at local universities and K-12 public schools). Store visits continued to decline until the week of April 19, 2020. The effect of the lockdown started to dissipate after mid-April, with visitor numbers to stores starting to increase. All retail businesses were allowed to operate normally after May 12, 2020. Accordingly, we focused on three phases that occurred 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 3.2); they do not perfectly match the timeline of state regulations on lockdown and reopening.

3.2. Exploratory analysis: Spatial and temporal changes in visitors and traffic 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 visitors 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 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. Our sample consists of many stores with decreases in store visits as well as a small number of stores with 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 multiple categories of store types to account for their different levels of traffic, store characteristics, and most importantly, to understand how low-income and racial minority populations changed their travel behavior during this disruption.

4 RESULTS

4.1 Summary of temporal changes in store traffic

Figure 2 illustrates the absolute and relative changes in average weekly traffic by store types for the study period. The average weekly traffic started to decline from the week beginning on March 16 and continued to decline until the week of April 13 (the “lockdown phase”). Average weekly visitors started to increase from the week of April 20 onward (the “reopening phase”). The average changes in store visits during the lockdown period were dominated by the changes in big-box store visits and mid/high-end grocery store visits (Figure 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 (Figure 2b). However, the growth rate of visitors beginning in the week of April 20 is higher for big-box grocery stores than other store types, especially during the time period of April 20 to May 10 (the end of the week of May 4).

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

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 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 other 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 other local stores. There was little to no difference in customers' travel time to all three store types: on average, people spent 23-27 minutes to access grocery stores.

With regard to travelers' 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.

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

	Big-box grocery stores		Mid/high-end grocery stores		Dollar stores		Other stores	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
<i>Store characteristics</i>								
Employee size	251	121	120	85	10	11	15	35
Sales volume	39748	19178	26795	19656	1319	706	6696	19156
<i>Local characteristics of store locations</i>								
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
<i>Average weekly visitors</i>								
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
<i>Change in average weekly visitors</i>								
Lockdown vs. pre-lockdown	-281	101	-90	86	-25	24	-14	20
Reopening vs. pre-lockdown	-205	94	-80	79	-21	21	-14	20
<i>Average trip length (minutes)</i>								
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
<i>Household income less than \$50k</i>								
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%
<i>Percentage of white travelers</i>								
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%

	Big-box grocery stores		Mid/high-end grocery stores		Dollar stores		Other stores	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
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%

4.2 Exploratory analysis of spatial and temporal changes in store visits

Figure 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 other stores as compared to big-box grocery stores and mid/high-end grocery stores (Figure 3a). During the reopening phase (Figure 3b), the proportional change for mid/high-end, dollar, and other grocery stores is greater as compared to the changes in the big-box grocery stores.

Figure 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).

Figures 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 (Figures 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 (Figure 4b). For mid/high-end grocery stores, the decline in OD traffic flow was more

pronounced in the reopening phase from nearby origins and some distant origins of Columbus (e.g., northeastern parts; Figure 4d).

O-D flow to big-box stores

O-D flow to mid/high-end stores

Figure 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)

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 other stores during both lockdown and initial reopening phases (Figures 5). For other neighborhoods,

most dollar stores experienced a higher decline in incoming traffic flow during the lockdown phase; some of these declines persisted in the reopening phase (Figure 5a and 5b). 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 other local stores that are in close proximity to mid/high-end grocery stores (Figure 5c and 5d).

O-D flow to dollar stores

O-D flow to other stores

Figure 5: Changes in OD flows to dollar stores (top panel) and to other stores (bottom panel)

between pre-lockdown and lockdown phase (a, c) and between pre-lockdown and initial

reopening phase (b, 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 ($OR_{\text{lockdown}} = 0.94$, $OR_{\text{reopening}} = 0.95$, $p < 0.05$). 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 ($OR_{\text{reopening}} = 0.02$, $p < 0.05$).

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 other 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 visitors was 53% (132 visitors) for mid/high-end grocery stores, 84% (39 visitors) for dollar stores, and 90% (28 visitors) for other 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, stores with higher percentages of low-income visitors had a lower magnitude of decline ($IRR_{\text{lockdown}} = 0.10$, $p < 0.05$) than stores with higher percentages of white travelers ($IRR_{\text{lockdown}} = 0.37$, $p < 0.05$). However, neither travelers' characteristics nor local characteristics of stores show statistically significant effects on the decline in store visitors during the reopening phase.

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
Other 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

	Model 1: Decline between pre-lockdown and lockdown phases			Model 2: Decline between pre-lockdown and initial reopening phases		
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
Other 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).

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 “other stores” category, 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 this “other” category 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 other local stores in certain areas of Columbus. In summary, 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: 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.

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 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, big-box and mid/high-end grocery stores experienced a recovery of nearby visitors but not those who traveled long distances during the reopening phase. In contrast, the visitor decline for dollar stores and other grocery 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 are more likely

to do so than their lower-income counterparts who have 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 other local stores. Meanwhile, our models indicated that, while the percentage of low-income and percentage of white customers were negatively associated with traffic decline 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 suggest a smaller magnitude of decline in stores visited by low-income and white populations. This also implies 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 other stores for their grocery shopping needs. Furthermore, similar to the findings of LeDoux & 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 & 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 & 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 a barrier 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 reopening phase. In contrast, suburban areas were more likely to see a slower recovery of grocery store visits during the reopening 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 effect (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 traffic flow data was limited to parcel sizes, resulting in an underestimation in the area size of big-box and mid/high-end grocery stores (which may occupy more than one parcel) and overestimation in the size of dollar and local stores (which may share the same parcel with other businesses). Second, measurement errors exist as visitors to big-box stores may have shopped for non-grocery products. Third, online shopping data were not available in this study. For big-box and mid/high-end grocery stores that offer online shopping 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 practice, 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 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 local stores, mid/high-end grocery stores, big-box grocery stores, and dollar stores. We found that 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 implies 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 will benefit marginalized populations.

Our study contributes to enhancing our understanding of how various socio-economic and built environment characteristics influence food shopping patterns during a major disruption.

Furthermore, it can contribute 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 areas and local businesses that are impacted the most in coping with and recovering from COVID-19 and its associated economic downturn. Insights from this study can also support the preparation 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:** Writing - Review & Editing. **HTKL:** Conceptualization, Methodology, Investigation, Writing - Original draft, Writing - Review & Editing, Supervision.

Acknowledgments

We thank the Ohio Department of Transportation (ODOT) for providing access to the StreetLight data within the state of Ohio.

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