



Changes of Grocery Shopping Frequencies and Associations with Food Deserts during the COVID-19 Pandemic in the United States

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Abstract The COVID-19 pandemic has dramatically altered people’s lives in multiple aspects, including grocery shopping behaviors. Yet, the changing trend of grocery shopping frequencies during the COVID-19 and its associations with food deserts remain unclear. We aimed to (1) examine variations of grocery shopping frequencies at county level in the USA during the COVID-19 pandemic from March 2020 to December 2021; (2) investigate associations between grocery shopping frequencies and food deserts during the COVID-19 pandemic; and (3) explore heterogeneity in grocery shopping frequencies—food desert associations across urban and rural areas. The county-level grocery

shopping frequencies were derived from a grocery pattern dataset obtained from SafeGraph. We divided the 22-month period into 5 stages and employed the growth curve modeling to estimate the trajectories of grocery shopping frequencies and the associations between grocery shopping frequencies and food deserts in each stage, separately. Results revealed that grocery shopping frequencies experienced a “W-shaped” pattern from March 2020 to December 2021. Counties with the least percent of food deserts had slower decrease in grocery shopping frequencies at the initial stage and recovered more rapidly at later stages. Counties with the highest percent of food deserts were subject to deprivation amplification as a result of the pandemic. We also found differences existed in the grocery shopping frequencies—food desert associations between metropolitan counties and rural counties. Our findings suggest the impacts of COVID-19 on grocery shopping

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frequencies varied across different time periods, shedding light on designing different strategies to reduce the risk of contagion while shopping inside of grocery stores. Further, our findings highlight an urgent need to help people living in food deserts (especially in rural counties) to procure healthy foods safely during health emergencies like COVID-19 pandemic which disrupt mobility and social behaviors.

Keywords Grocery shopping frequency · Food deserts · Temporal changes · Urban-rural differences · COVID-19 · Longitudinal study

Introduction

The COVID-19 pandemic has dramatically altered people's daily activities [1, 2]. People reduced daily activity trips at the early stage of the COVID-19 pandemic in response to social distancing policies [3, 4]. The COVID-19 pandemic and social distancing policies may increase people's concerns toward visiting brick and mortar grocery stores [1]. Grocery shopping serves as a potential pathway to link healthy food environment, healthy eating, and health outcomes (i.e., obesity) [5–7]. Poorer access to healthy food outlets is associated with lower frequencies of healthy food purchase and consumption [8–10]. People who live in “food deserts” (areas with poorer access to healthy foods) face more barriers (i.e., limited options of transportation) to procure healthy foods [11]. The health benefits of grocery shopping are particularly important in the context of the COVID-19 pandemic because healthy eating could boost immune system to prevent or fight against the coronavirus infections [12]. The impact of the COVID-19 pandemic on grocery shopping behaviors may be even stronger for people living in food deserts [13]. The restriction policies of mobility lead to major transit demand decline at the early stage of the COVID-19 pandemic [14, 15]. It would be particularly difficult for those who live in food deserts and do not own private cars to visit supermarkets that are far away from home. Thus, understanding changes of grocery shopping frequencies and their associations with food deserts during the COVID-19 pandemic could shed light on designing and implementing effective strategies to help people procure healthy food safely.

Besides, the associations between grocery shopping behaviors and food environment may vary

between urban and rural areas. Some studies found that urbanicity was correlated with healthy food access [16, 17]. Empirical evidence illustrates that supermarket access has different impacts on fruit and vegetable intake in urban and rural settings [18]. In addition, the impacts of stay-at-home orders on the COVID-19 infection rates and mortality vary between urban and rural counties [19]. The reduction of grocery trips during the COVID-19 pandemic also varies depending on level of compactness [20]. Thus, it is necessary to examine the heterogeneity in associations between change of grocery shopping frequencies and food deserts across urban and rural areas.

Grocery shopping frequencies were also associated with sociodemographic characteristics including poverty level, age groups, and population density [2, 21, 22]. The temporal changes of grocery shopping frequencies may vary across different sociodemographic groups during the COVID-19 pandemic. For instance, empirical evidence elucidates that higher income people experienced greater decline in grocery store visits at the early stage of the COVID-19 pandemic [23]. Additionally, empirical literature indicates that political preference influences the change of overall mobility level during the COVID-19 pandemic. Comparing with Republican counties, Democratic counties have greater reduction in daily activity trips [3] and engage more social distancing [24] during the early stages of the pandemic. Thus, political preference may impact grocery shopping trip frequencies as well.

A growing number of studies have investigated the changes in grocery shopping patterns during the COVID-19 pandemic. One study found grocery store visits declined below the baseline within a week from March 13 and started recovering in some states by the end of May [25]. Another study illustrated that supermarket visits for poorer neighborhoods in the USA had larger decline during the early stage of the COVID-19 pandemic [23]. A few other studies found that grocery shopping trips were disrupted during the early stage of COVID-19 restrictions in England [26], Greek [27], and China [2].

Despite growing evidence on change of grocery shopping patterns at the early stage of the COVID-19 pandemic, there are some limitations in the current literature. First, most studies focused on change of grocery shopping behaviors at the initial stages of the COVID-19 pandemic. However, the COVID-19 pandemic may have long-term impacts on people's grocery shopping behaviors. It is essential to understand how

people interact with food environment during a longer time period of the pandemic. Second, while most studies examined how people changed their grocery shopping behaviors in response to the COVID-19 health emergencies, evidence on associations between grocery shopping frequencies and food deserts remains scarce. Further, the knowledge on heterogeneity in associations between grocery shopping frequencies and food deserts between urban and rural areas is limited.

To bridge the gaps, this study aimed to investigate the temporal variations of county-level grocery shopping frequencies in the USA and their associations with food deserts during a 22-month period of the COVID-19 pandemic using a longitudinal design. We aimed to (1) examine variations of grocery shopping frequencies at county level in the USA from March 2020–December 2021; (2) investigate associations between grocery shopping frequencies and food deserts during the COVID-19; and (3) explore heterogeneity in grocery shopping frequencies—food desert associations across urban and rural areas.

Methods

Study Setting

Our study site was the conterminous United States. We filtered out supermarkets/grocery stores with missing information on monthly visits and excluded those located in Hawaii and Alaska. The selection yielded 70,326 supermarkets/grocery stores in 2984

counties in the conterminous United States. We classified the counties by rurality into three categories: metropolitan, micropolitan, and rural [28, 29] based on the urban influence codes (UIC) collected from the USDA [30]. Metropolitan counties included large metropolitan areas of more than 1 million residents (UIC = 1) and small metropolitan areas of less than 1 million residents (UIC = 2). Micropolitan counties included micropolitan areas and those adjacent to either a large or small metropolitan areas (UIC = 3, 5, and 8). Rural counties were those non-core areas adjacent to large or small metropolitan or micropolitan areas (UIC = 4, 6, 7, and 9–12). Figure 1a displays the spatial context of the rurality of counties and food deserts across the conterminous United States.

Grocery Shopping Data

The grocery shopping frequencies came from the pattern dataset of SafeGraph [31]. SafeGraph is a company that provides places dataset collecting from anonymized sample of smartphone users. The patterns' dataset included information like name, category, monthly number of visits to each point of interest, and the longitude/latitude coordinates for each point of interest in the USA. We focused on the monthly county-level grocery shopping frequencies in the USA from March 2020 to December 2021. Some recent studies have argued that the patterns dataset from SafeGraph were accurate and comprehensive for retail locations in the USA [32, 33]. We

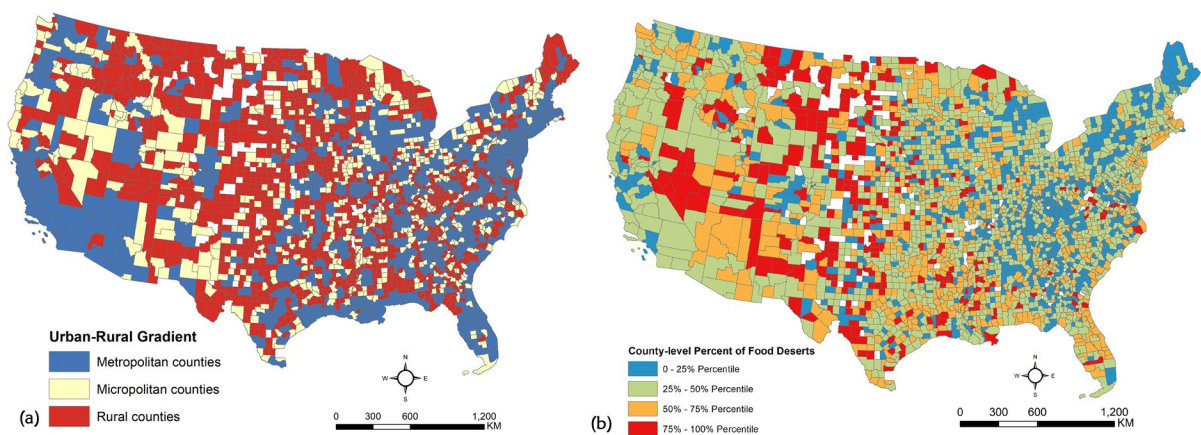


Fig. 1 Spatial context of the study area across urban-rural gradients (a) and the percent of food deserts at county level (b)

calculated the county-level monthly grocery shopping frequencies by summing up the monthly visits of each supermarket/grocery store located in the corresponding county in each calendar month during March 2020 and December 2021. We further standardized the county-level monthly grocery shopping frequencies by 1000 people. We log-transformed the county-level monthly grocery shopping frequencies by 1000 people in analytical models since it was skewed to the right.

Food Deserts

We adopted the definition of food desert from the USDA metric of low-access tract measured at 1 mile and 10 miles [34]: a census tract was considered as a food desert if at least 500 people or 33% of the population living more than 1 mile in urban areas or more than 10 miles in rural areas from the nearest supermarket, supercenter, or large grocery store. This metric is a widely used definition by the USDA and has been used in previous research [35]. There were 27,337 census tracts that were considered as food deserts in the 48 states in the USA as of the year of 2019. We calculated the percent of census tracts that were considered as food deserts in each county and categorized the percent of food deserts at county level into quartile for analytical models. Figure 1 geovisualizes the percent of food deserts at county level in the USA (Fig. 1b).

Covariates

We included county-level new confirmed cases of COVID-19, percent of people who voted for Democratic Party in the 2020 Presidential Election, state-level stringency index, percent of population below poverty, percent of population aged 65 or above, percent of African American/black, and population density as covariates. The new confirmed cases of COVID-19 came from Centers for Disease Control and Prevention and were downloaded from USA facts [36]. We standardized the number of new COVID-19 cases by 1000 people at each county and log-transformed it in analytical models. The state-level stringency index was used as a proxy for restriction policy for mobility, which came from the Oxford COVID-19 Government Response Tracker [37]. The state-level stringency index represented the extent to

the strictness of restriction policies aiming to limit people's mobility level for each state. Higher scores indicate that the restriction policies for mobility are stricter. We calculated the mean values of the stringency index for different stages in analytical models. The 2020 Presidential Election data came from <https://github.com/tonmcg> [38]. The political preference was represented by percent of population who voted for Democratic Party in the 2020 Presidential Election. The sociodemographic data at county level in the USA came from the 2019 American Community Survey [39].

Statistical Analyses

We employed descriptive statistics to describe monthly grocery shopping frequencies at county level, percent of food deserts at county level, and a set of covariates. We employed growth modeling approach to estimate the temporal variations in grocery shopping frequencies and their associations with food deserts adjusting for covariates. We employed a multilevel modeling framework to detect the within-county differences at level 1 and between-county differences at level 2 [40]. We split the temporal period between March 2020 and December 2021 into five stages based on the change trend of the grocery shopping frequencies along with the COVID-19 new cases [3]: stage 1 ranged from March 2020 to April 2020; stage 2 ranged from April 2020 to July 2020; stage 3 ranged from July 2020 to February 2021; stage 4 ranged from February 2021 to July 2021; and stage 5 ranged from July 2021 to December 2021.

We employed linear growth model to examine the change trends of grocery shopping frequencies and estimate their associations with food deserts during each stage separately. The outcome variable in each stage was the monthly total number of grocery shopping frequencies per 1000 people at county level (log-transformed) during the corresponding time period respectively. We further adjusted time invariant covariates at level 2, including total new COVID-19 cases per 1000 people in each stage (log-transformed), mean stringency index during each stage, percent of population who voted for Democratic Party for the 2020 Presidential Election, percent of population aged 65 or above, percent of population below poverty, and population density (log-transformed). Note that we adjusted for time invariant covariates

in growth modeling to make sure that the models can converge with interpretable results [40].

The general form of linear growth model adjusting time invariant covariates is displayed in the following equations [40]:

$$\log(Y_{it} + 1) = b_{1i} + b_{2i} \cdot t + u_{it} \tag{1}$$

$$b_{1i} = \beta_1 + \beta_{1i_0} \cdot FD + \sum \beta_{1i_j} \cdot X_j + d_{1i} \tag{2}$$

$$b_{2i} = \beta_2 + \beta_{2i_0} \cdot FD + \sum \beta_{2i_j} \cdot X_j + d_{2i} \tag{3}$$

where Y_{it} denotes the total number of grocery shopping per 1000 people in each month; t is the months during each stage; b_{1i} is a random-effect intercept; b_{2i} denotes a random-effect linear slope for county i ; β_1 is a fixed-effect intercept; FD denotes the percent of food deserts in a county; β_{1i_0} is a fixed-effect coefficient for healthy food access on the random-effect intercept; X_j denotes the j th time-invariant covariate; β_{1i_j} is a fixed-effect coefficient for X_j on the random-effect intercept; β_2 is a fixed-effect change rate over time; β_{2i_0} is a fixed-effect coefficient for healthy food access on the random-effect slope; β_{2i_j} is a fixed-effect coefficient for X_j on the random-effect

slope; d_{1i} , and d_{2i} are county i 's deviations from the fixed effects.

We further stratified the analytical sample by urban-rural gradient (metropolitan, micropolitan, and rural) to assess whether the associations between grocery shopping frequencies and food deserts were divergent across urban-rural gradients.

Results

Descriptive Statistics

Figure 2 displays the mean grocery shopping frequencies along with the total count of COVID-19 new cases and mean stringency index at county level from March 2020 to December 2021. The mean total number of grocery frequencies per 1000 people in the starting and ending time points of March 2020, April 2020, July 2020, February 2021, July 2021, and December 2021 were 91.16, 75.57, 95.25, 75.9, 105.97, and 101.94, respectively. The total new cases of COVID-19 per 1000 population experienced fluctuations, too. The number of new cases increased from March 2020 and reached its peak in December 2020. The number of new cases decreased slightly

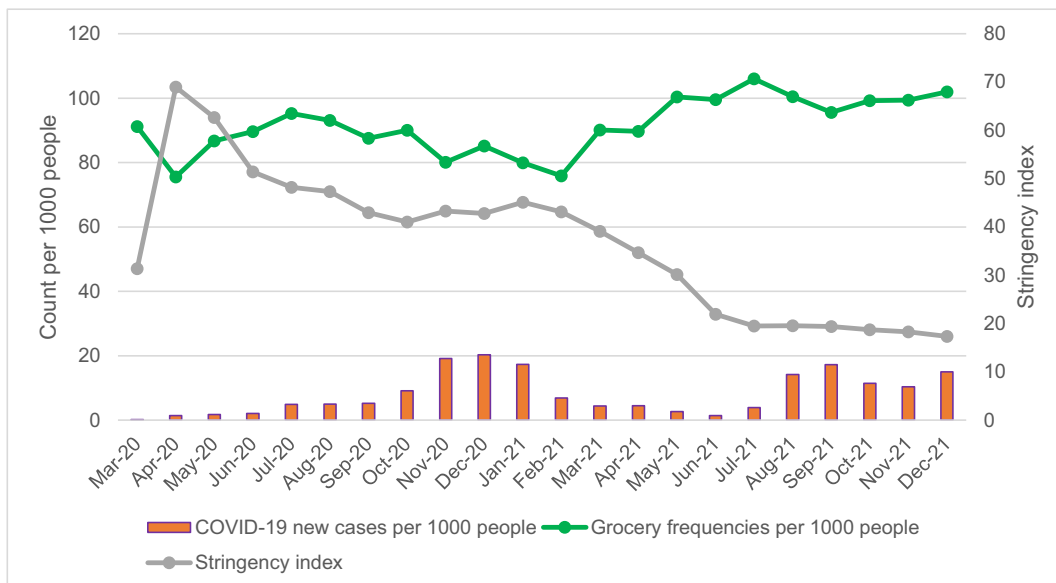


Fig. 2 Mean values of monthly grocery shopping frequencies per 1000 people, COVID-19 new cases per 1000 people, and mean stringency index from March 2020 to December 2021

from December 2020 to March 2021. Then, it had a sharp decrease from March to June 2021. After June 2021, the total number of cases increased again and climbed to a new peak in December 2021. Meanwhile, the mean state-level stringency index was 31.35 in March 2020 and reached to its peak in April 2020 (mean = 68.98). It started decreasing from May 2020 to December 2021.

Table 1 displays descriptive statistics for percent of food deserts at county level and sociodemographic characteristics. The mean percent of food deserts at county level was 43.31 (standard deviation [SD] = 26.88). The mean county-level percent of people that were below poverty level was about 15%. The mean percent of population who aged 65 or above was about 19%. The mean county-level percent of

population who voted for Democratic Party in the 2020 Presidential Election is 34%. The mean population density was 88.67/km² (SD = 488.50/km²).

Temporal Changes in Grocery Shopping Frequencies During the COVID-19 Pandemic

Table 2 displays the temporal variation in grocery shopping frequencies during the COVID-19 pandemic. In general, the monthly total grocery shopping frequencies fluctuated like a “W” shape, with a sharp decrease at the early stage of the pandemic (March–April 2020), an increase from April 2020 to July 2020, a decrease from July 2020 to February 2021, an increase from February to July 2021, and little variation from July 2021 to December 2021.

Table 1 Descriptive statistics for food deserts and sociodemographics

Variables	Mean (SD)
Food deserts	
Percent of food deserts at county level	43.31 (26.88)
Sociodemographic characteristics at county level	
% of population aged 65 and above	19.4 (4.66)
% of Democratic voting in the 2020 Presidential Election	33.6 (15.75)
% of population below poverty	14.66 (6.09)
Population density (/km ²)	88.67 (488.50)

Table 2 Temporal variations of grocery shopping frequencies and associations with food deserts during March 2020–December 2021

	Stage 1: Mar 20–Apr 20	Stage 2: Apr 20–Jul 20	Stage 3: Jul 20–Feb 21	Stage 4: Feb 21–Jul 21	Stage 5: Jul 21–Dec 21
Intercept					
Intercept	4.32***	3.83***	4.20***	3.66***	3.96***
% of census tracts that were food deserts					
1st quartile vs. 4th quartile	- 0.04	- 0.03	0.01	- 0.14**	0.19**
2nd quartile vs. 4th quartile	0.02	0.03	0.02	0.02	0.06
3rd quartile vs. 4th quartile	0.06	0.06	0.06	0.04	0.13
Slope					
Slope	- 0.08*	0.04*	- 0.07***	0.03***	0.01
% of census tracts that were food deserts					
1st quartile vs. 4th quartile	0.02*	0.01*	- 0.003	0.01***	- 0.01**
2nd quartile vs. 4th quartile	0.01	- 0.001	0.002	0.002	- 0.001
3rd quartile vs. 4th quartile	0.005	0.002	0.002	0.003	- 0.002

Each model adjusted for county-level new confirmed cases of COVID-19, percent of people who voted for Democratic Party in the 2020 Presidential Election, state-level stringency index, percent of population below poverty, percent of population aged 65 or above, percent of African American/black, and population density

< 0.1; * < 0.05; ** < 0.01; *** < 0.001

At stage 1 (March–April 2020), the grocery shopping frequencies experienced a sharp decrease from March to April 2020 (slope = -0.08 , $p < 0.001$). The grocery shopping frequencies started recovering from April to July 2020 with a positive slope (slope = 0.04 , $p < 0.001$). The grocery shopping frequencies decreased again from July 2020 to February 2021 (slope = -0.07 , $p < 0.001$) and increased again from February 2021 to July 2021 (slope = 0.03 , $p < 0.001$). They experienced little variation from July 2021 to December 2021.

Grocery Shopping Frequencies and Food Deserts During the COVID-19 Pandemic

Table 2 also shows adjusted associations between grocery shopping frequencies and food deserts over time. The full table with covariates is shown in Supplement Table 1. Comparing with counties with higher percent of food deserts (the 4th quartile), counties with the fewest percent of food deserts (1st quartile) had slower decrease in grocery shopping frequencies at stage 1 (slope = 0.02 , $p < 0.05$) and faster increase in grocery shopping frequencies at stage 2 (slope = 0.01 , $p < 0.05$) and stage 4 (slope = 0.01 , $p < 0.05$), respectively. There was no strong evidence showing that food deserts were associated with changes of grocery shopping frequencies at stage 3 and stage 5.

Differences in Associations Between Grocery Shopping Frequencies and Food Deserts by Rurality

There existed heterogeneity in the changes of grocery shopping frequencies and the associations with food deserts across metropolitan, micropolitan, and rural counties (see Table 3). Regarding the changes of grocery shopping frequencies, the metropolitan counties had little variations at stage 1 and 2, decreased at stage 3, and recovered at stages 4 and 5. The micropolitan counties had the “W”-shaped change trend from stage 1 to stage 5. Meanwhile, the rural counties experienced decreases in grocery shopping frequencies from stage 1 to stage 3, and did not recover at stages 4 and 5. We observed differences in the associations between grocery shopping frequencies and food deserts between metropolitan counties and rural counties. Fewer percent of food deserts (1st quartile) was associated with higher grocery shopping frequencies in rural counties, whereas fewer percent of food

deserts (1st quartile) was associated with lower grocery shopping frequencies in metropolitan counties.

Discussion

This study aimed to investigate temporal variations of grocery shopping frequencies at county level in the USA during the COVID-19 pandemic and the associations with food deserts. First, grocery shopping frequencies experienced a “W-shaped” change pattern during March 2020–December 2021. Second, counties with fewer percent of food deserts had slower decrease and faster increase in grocery shopping frequencies during the COVID-19 pandemic. Third, the associations between grocery shopping frequencies and food deserts varied across urban-rural gradients.

Change Patterns of Grocery Shopping Patterns During the COVID-19 Pandemic

The change rates in grocery shopping frequencies experienced fluctuations from March 2020 to December 2021, suggesting that the impacts of COVID-19 pandemic on grocery shopping varied across different time periods. The grocery shopping frequencies had a sharp decrease during March–April 2020, indicating that people reduced grocery frequencies at the early stage of the COVID-19 pandemic. This result is consistent with the change trends of grocery shopping frequencies at the initial stage of the COVID-19 pandemic in previous studies [1, 41]. One potential reason may be because people were following social distancing policies at the early stage of the pandemic and reduced their mobility level altogether [23, 42]. Further, people may switch to purchase food online during the initial stage of the COVID-19 pandemic [43, 44], which may subsequently reduce grocery shopping trips [45]. The grocery shopping frequencies started recovering from April to July 2020 despite of the increasing trend of new confirmed cases of COVID-19. This pattern is consistent with the overall mobility pattern in the USA during this time period [3]. The grocery shopping frequencies decreased from July 2020 to February 2021. One potential reason is that the increasing trend of the COVID-19 new cases and mortality rate makes people less willing to visit grocery stores during this time period [46]. The grocery shopping frequencies

Table 3 Disparities in associations between grocery shopping frequencies and food deserts across urban and rural counties

	Stage 1: Mar 20– Apr 20	Stage 2: Apr 20–Jul 20	Stage 3: Jul 20– Feb 21	Stage 4: Feb 21–Jul 21	Stage 5: Jul 21–Dec 21
Metropolitan counties					
Intercept					
Intercept	4.12***	3.88***	3.75***	3.45***	2.78***
% of census tracts that are food deserts					
1st quartile vs. 4th quartile	− 0.12*	− 0.12*	− 0.12*	− 0.17*	0.05
2nd quartile vs. 4th quartile	0.00	0.00	− 0.02	0.03	− 0.04
3rd quartile vs. 4th quartile	0.08	0.08	0.07	0.13*	0.07
Slope					
Slope	0.00	0.03	− 0.04**	0.03**	0.06**
% of census tracts that are food deserts					
1st quartile vs. 4th quartile	0.01	0.00	0.00	0.004	− 0.009*
2nd quartile vs. 4th quartile	0.00	0.00	0.00	0.00	0.00
3rd quartile vs. 4th quartile	0.00	0.00	0.00	0.00	− 0.00
Micropolitan counties					
Intercept					
Intercept	3.50***	2.67***	4.05***	2.53***	4.80***
% of census tracts that are food deserts					
1st quartile vs. 4th quartile	− 0.11	− 0.08	− 0.07	− 0.24*	0.02
2nd quartile vs. 4th quartile	0.10	0.14 [#]	0.15 [#]	0.04*	0.13
3rd quartile vs. 4th quartile	0.14	0.12	0.11	0.06	0.09
Slope					
Slope	− 0.13 [#]	0.11***	− 0.06**	0.04*	− 0.08**
% of census tracts that are food deserts					
1st quartile vs. 4th quartile	0.05*	0.01	0.00	0.01**	0.00
2nd quartile vs. 4th quartile	0.03	0.00	0.00	0.01	0.00
3rd quartile vs. 4th quartile	0.01	0.00	0.00	0.01	0.00
Rural counties					
Intercept					
Intercept	4.85***	4.22***	4.63***	4.14***	4.13***
% of census tracts that are food deserts					
1st quartile vs. 4th quartile	0.16*	0.17*	0.22**	0.05	0.40***
2nd quartile vs. 4th quartile	0.05	0.07	0.03	0.06	0.19
3rd quartile vs. 4th quartile	− 0.00	− 0.00	0.00	− 0.07	0.17
Slope					
Slope	− 0.13 [#]	− 0.01	− 0.07**	0.01	0.03
% of census tracts that are food deserts					
1st quartile vs. 4th quartile	0.02	0.01	− 0.01	0.01*	− 0.01*
2nd quartile vs. 4th quartile	0.02	− 0.01	0.00	0.00	− 0.008
3rd quartile vs. 4th quartile	0.00	0.00	0.00	0.01	− 0.01

Each model adjusted for county-level new confirmed cases of COVID-19, percent of people who voted for Democratic Party in the 2020 Presidential Election, state-level stringency index, percent of population below poverty, percent of population aged 65 or above, percent of African American/black, and population density

< 0.1; * < 0.05; ** < 0.01; *** < 0.001

started to recover again from February to July 2021, and did not change much from July 2021 to December 2021. People may get tired of the coronavirus and have quarantine fatigue after a 12-month period [47–49]. In addition, people's risk perception of the coronavirus decreased over time [2, 50, 51], which could potentially encourage more grocery shopping trips at a later stage of the COVID-19 pandemic. The temporal variations of grocery shopping frequencies will inform policymakers to carefully design and implement mobility restrictions and hygienic practices corresponding to different stages to reduce the risk of contagion while purchasing foods inside of supermarkets.

Associations Between Grocery Shopping Frequencies and Food Deserts During the COVID-19 Pandemic

We found that counties with the least percent of food deserts had slower decrease in grocery shopping frequencies at the initial stage and recovered more rapidly in grocery shopping frequencies at later stages of the COVID-19 pandemic. It indicates that counties with the highest percent of food deserts are subject to deprivation amplification as a result of the pandemic. This finding suggests that higher food access could encourage people to visit brick and mortar supermarkets more frequently even in the context of the COVID-19 pandemic. This result resonates with a previous finding that areas with lower supermarket density has greater reduction of trip frequencies during the COVID-19 pandemic [52]. This finding is particularly important in the context of the COVID-19 pandemic, highlighting that those living in food deserts might face more severe barriers to visit supermarkets to procure healthy foods. For instance, the mobility restrictions could mitigate the overall mobility level at the early stage of the COVID-19 pandemic [3, 53], which may potentially discourage people to visit supermarkets that were far away from home. Also, empirical evidence illustrates that people who lived in areas with limited food access had higher reliance on motorized trips to visit supermarkets [54]. However, people were less likely to take public transit since they were in fear of contracting the coronavirus during the COVID-19 pandemic [15, 55]. The decline in transit ride may make it more difficult for those living in food deserts to get to supermarkets

beyond their immediate neighborhoods due to limited transportation options [35]. Our findings highlight the urgent need to help those living in food deserts to procure healthy foods safely during health emergencies like the COVID-19 pandemic which disrupt people's lives dramatically.

Heterogeneity in Associations Between Grocery Shopping Frequencies and Food Deserts by Rurality

We observed heterogeneity in the associations between grocery shopping frequencies and food deserts between metropolitan counties and rural counties. Lower percent of food deserts was associated with higher grocery shopping frequencies in rural counties. This result suggests that rural counties with higher percent of food deserts have lower grocery shopping frequencies during the COVID-19 pandemic. This result is in line with previous findings that higher healthy food access is related with higher grocery shopping frequencies [9]. It highlights the importance of improving healthy food access in rural counties during the COVID-19 pandemic to encourage higher grocery shopping frequencies, which could potentially reduce food access inequity. Meanwhile, metropolitan counties with lower percent of food deserts had lower grocery shopping frequencies. This result indicates that metropolitan counties with higher healthy food access had lower grocery shopping frequencies. One potential reason is that people in metropolitan counties may have lower pandemic fatigue level [48] and thus are more likely to follow the stay-at-home order to reduce grocery shopping trips during the COVID-19 pandemic. A previous study illustrates that compactness leads to a significantly higher reduction in grocery and transit trips [20]. Nevertheless, the heterogeneity in grocery shopping frequency—food desert associations highlight future research needs to investigate the relationships between grocery shopping frequencies and food deserts in various spatial contexts [56].

Limitations

This study also had some limitations. First, the COVID-19 new cases were only available at county level; therefore, we aggregated grocery shopping

frequencies at county level for analysis. Future research could investigate the grocery shopping frequencies at finer scales like census tract level or individual level. Second, we simplified the healthy food access by using food desert definition from the USDA, which is not sufficient to capture the full picture of food access. Some scholars have argued that food desert concept should incorporate a temporal component to better represent health food access and their associations with health outcomes [57]. Third, the percent of food deserts at county level was time-invariant during the 22-month period. Future study could measure the dynamic food environment during the COVID-19 pandemic to produce more robust associations between grocery shopping frequencies and healthy food access. Fourth, this study focused solely on the growth trajectories of grocery shopping frequencies, neglecting other dimensions of grocery shopping patterns. Future research could investigate change patterns of grocery shopping distances and shopping duration during the COVID-19 pandemic.

Conclusions

This study contributes to the literature on grocery shopping behaviors during the COVID-19 pandemic in two aspects. First, the temporal changes of grocery shopping frequencies in a 22-month period indicate that the COVID-19 pandemic impacts people's essential routine activities differently across different stages. This finding will inform policymakers that it is necessary to carefully design and implement COVID-19-related mobility restriction policies and hygienic practices at different stages to mitigate the contagion risk while shopping inside of supermarkets. Second, the associations between food deserts and grocery shopping frequencies during the COVID-19 pandemic highlight an urgent need to help people living in food deserts (especially in rural counties) to procure healthy foods safely in health emergencies like COVID-19 which disrupt movement and social behaviors dramatically.

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