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LOCKING UP RESTAURANTS: DID THE COVID-19 LOCKDOWNS SHIFT LONG-TERM U.S. CONSUMPTION HABITS?

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Abstract

COVID-19 affected individuals' lifestyle in every US state, however, 39 states responded to the pandemic by implementing stay-at-home orders. Through SafeGraph's foot traffic dataset, Patterns, we evaluate weekly frequency of visits to fast-food, dine-in restaurants, and grocery stores at the census tract level between January 2019 and May 2022. We estimate a two-way fixed effects difference-in-differences model to evaluate the effects of the stay-at-home policy on visitation to each food outlet. Our primary results show decreases in visits to all food establishments in census tracts with orders following March 2020. These effects are strongest for food-away-from-home establishments. We find similar changes in visitation patterns regardless of access. However, when comparing the share of visits by establishment type, we find substitutions from fast-food visits and restaurants visits. We find that these changes persist beyond the pandemic, independent of rurality, food access, or economic factors.
Keywords: *COVID-19, Consumer behaviour, Food retailing, Food Consumption, Restaurants, Public health*
JEL: Codes: *I18, D12, Q18*

1. Introduction

Fast-food consumption is associated with a range of negative health outcomes, yet its accessibility and convenience make it a staple in many diets. While past research has examined policy-driven efforts to curb fast-food intake—such as sugar taxes, information requirements, or zoning restrictions—less attention has been given to how external disruption alter food preferences and consumption patterns over time. Fast foods, which are often high in sugar, salt, and fats, are commonly criticized for their negative impact on health, while simultaneously appealing to consumer tastes. We hypothesize, however, that, in addition to these taste-based preferences, consumption of these foods is driven by convenience and availability.

This study if the COVID-19 lockdowns create lasting changes in consumer food habits**.** Using high-frequency foot traffic data, we analyze shifts in visits to fast-food restaurants, grocery stores, and dine-in restaurants before, during, and after pandemic-related restrictions. Unlike prior research that relied on self-reported survey data or short-term evaluations, our approach provides a detailed, long-term view of how mobility and food choices evolved. Using detailed foot traffic data, we examine visits to fast-food, dine-in restaurants, and grocery stores between January 2019 and May 2022, focusing specifically on how the levels and shares of visits between these establishments changed in the weeks following March 2020.

In recent years, federal, state, and local governments have implemented policies aimed at promoting healthier eating habits. For example, taxes have been imposed to reduce the consumption of sugary drinks (Cawley et al., 2019; Powell & Leider, 2021), requirements for nutritional information posting in restaurants have been introduced (Cawley et al., 2020), zoning regulations on fast-food restaurants have been implemented (Lydon et al., 2011), and public funding has been allocated to facilitate the entry of grocery stores into food deserts (Wright et al., 2016). Access to nutritious food has been shown to be a crucial determinant of encouraging healthier consumption behavior (Azétsop & Joy, 2013).

This study contributes to the existing literature on food consumption and access during and following the COVID-19 pandemic in several unique ways. First, we employ a novel data set containing detailed weekly visit information from census tracts to a variety of food outlets. This dataset provides a more substantial sample size than previous studies in this field, contributing to and re-enforcing findings. Second, due to the abrupt nature of COVID-19 and the policies combating the spread of the virus, we have a unique opportunity to evaluate an exogenous shift in consumption patterns without a parallel shift in preferences. Third, we consider the lasting impacts of a behavior shock by evaluating the impact of the lockdown policies on shifting consumption habit to specific venues of food even beyond the COVID vaccine rollouts. This study contributes to research on consumer patterns, preferences, and long-term behavioral effects of COVID-19-related disruptions.

Our results show that census tracts with stay-at-home policies in effect had a statistically significant 19.8% decline in visits to fast-food establishments, a 5.7% decline in grocery store visits, and an 18.3% decline in sit-down restaurants starting in March 2020 following the stay-at-home policies. These changes remained relatively consistent over time, even following the repeal of the initial stay-at-home order. This serves as additional evidence of longer-term changes for individuals with the initial behavior shock. Importantly, when comparing the share of visits by establishments, we find that the stay-at-home orders decreased the share of visits to fast food and sit-down restaurants, referred to as “away-from-home” consumption. This decline in away-from-home consumption is offset by a rise in the share of visits to grocery stores—although we cannot comment on the levels of purchases at these locations. Unlike the levels of visits, the effects on the share of visits to each establishment diminished in each subsequent period that we evaluated and generally returned to pre-pandemic levels.

Understanding whether these behavioral shifts are temporary or long-lasting has major implications for public health, urban planning, and food policy. If mobility changes during the pandemic permanently reshaped consumer habits, policymakers may need to rethink strategies for food access, regulation, and health interventions in a post-pandemic world. In the next section, we review relevant literature on food consumption patterns and the COVID-19 mobility shock. In Section III, we present the policies which changed access and convenience of fast-food and dine-in food venues and the data sources that our work draws from. In Section IV, we describe our methodology and in our final sections, we present our results, conclusions, and discuss the implications and avenues for future research.

1.1. Literature Review

Over the past few decades, there have been notable shifts in food consumption patterns. Consumption has steadily shifted from in-home dining to away-from-home dining(Lin & Guthrie, 2013; Todd, 2017). Between 2013 and 2016, more than 36% of adults consumed fast-food on any given day (Fryar et al., 2018), and food-away-from-home accounted for over one-third of total calorie intake (Todd, 2017). Most adults report frequenting a fast-food restaurant at least once a week (Garza et al., 2016) and approximately half of all food spending is away-from-home (Saksena et al., 2018).

However, away-from-home consumption is associated with a lower quality of overall diet. Food prepared at-home generally exhibits superior nutritional qualities when compared to food consumed away-from-home (Saksena et al., 2018). Food-away-from-home encourages larger portion sizes (Nielsen & Popkin, 2003), higher caloric intake (Fryer & Ervin, 2013), and lower diet quality (Todd, 2017). In contrast, food prepared at home tends to be lower in saturated fats and sugars and higher in fiber, iron, and calcium (Guthrie et al., 2002; Wolfson et al., 2020; Wolfson & Bleich, 2015).

Furthermore, fast-food consumption is linked to a wide range of negative health outcomes (Mohiuddin, 2020; Sobhani et al., 2021). Frequent fast-food consumption is associated with higher BMI, developmental diabetes, cardiovascular disease, increased risk of stroke, and acute cardiac arrest (Alter & Eny, 2005; Bahadoran et al., 2015; Morgenstern et al., 2009). Although much of the literature on dietary venues examines the role of fast-food access, other researchers have shown that sit-down restaurant consumption tends to be higher in calories, fats, cholesterol, and sodium than food consumed at-home (An, 2016).

Consumer decisions for away-from-home consumption tend to be driven by impulsivity and convenience (Eckert & Vojnovic, 2017; Garza et al., 2016). Other consumers report that the lower prices (Lusk & Briggeman, 2009) and tastes (Saksena et al., 2018) drive fast-food consumption. Researchers have also found that availability and access to different food venues also play a significant role in consumption decision, although this effect is less pronounced for full-service restaurants (Currie et al., 2010; Fleischhacker et al., 2011; Saksena et al., 2018).

The COVID-19 pandemic broadly changed the levels of availability and access to these different food venues for many consumers in the months following March 2020, particularly for those with Stay-At-Home orders. Restaurant dining was no longer convenient or easily accessible, requiring similar effort to other venues of consumption. We find that this disruption acted as a shock to consumers' habits. This paper contributes to literature on the COVID-19 pandemic by examining the effects of the policy and this consumption habit shock.

Across all industries, consumer behavior changed during the COVID-19 pandemic (Mendez-Carbajo, n.d.), particularly in the context of food consumption (Chenarides et al., 2021; Dube et al., 2021). Studies have shown differing results in the months following March 2020. While overall food expenditures declined (Goddard, 2021) several studies found that food-at-home consumption and grocery purchases increased during the COVID-19 pandemic (Chenarides et al., 2021; Ellison et al., 2022). During the pandemic, people relied more heavily on groceries, resulting in increased time spent cooking at home (Cummings et al., 2022). Zeballos & Dong (2021) estimate that although unemployment played a large factor, the decrease in away-from-home spending largely resulted from pandemic policy.

There has been robust literature discussing the impact that COVID-19 has on the future of online and in-person shopping. Ellison et al. (2022) shows that in-person grocery shopping remained a critical aspect of food acquisition during and following the pandemic. The authors note; however, online grocery shopping has been shown to supplement in-person grocery shopping. Younes et al. (2022) shows a large return to in-person shopping after the initial months of the pandemic but also shows that many consumers elect for continued online shopping. An online survey in June 2020 shows that 55% of households were participating in online shopping.

Jensen et al. (2021) estimate that 58% intended to continue shopping online even after the pandemic. Li et al. (2023) use Safegraph *Patterns* to show large changes in grocery visits in the initial time of the pandemic that evened in the later time. Although online grocery shopping experienced a surge during the pandemic, it still constituted a relatively small portion of total food expenditures.

Despite the increase in food-at-home expenditures, weight gain was broadly reported in the United States (Bhutani et al., 2021; Cao et al., 2022; Freedman et al., 2022; Goitia et al., 2022; Khubchandani et al., 2022; Seal et al., 2022; Woolford et al., 2021; Zachary et al., 2020; Zeigler, 2021) and in other countries (Cena et al., 2021; Daniel et al., 2022; Sidor & Rzymski, 2020). Some studies recognize the impact of poor sleep habits, anxiety, and depression on weight gain during this period (Khubchandani et al., 2022; Seal et al., 2022; Zachary et al., 2020). Other studies theorize that, in addition to diet, a lack of physical activity was also an important mechanism for weight-gain during the pandemic (Daniel et al., 2022; Robinson et al., 2021; Zachary et al., 2020).

State governments implemented policies with varying levels of intensity in response to the COVID-19 crisis. These policies impacted food-away-from-home consumption decisions across all states. However, the extent to which consumers faced access constraints varied among the states. Relatively little research has been conducted on the long-term impact of COVID-19's Stay-At-Home policies on fast-food visitation or consumption. A study by Yang et al. (2020) shows a drop in restaurant demand in the immediate weeks following the implementation of the Stay-At-Home orders and a further drop resulting from additional cases of COVID-19. These authors use foot traffic data from visitdata.org and Facteus's credit card transaction data to analyze changes in daily restaurant demand at the county-level from February 2020 to May 2020. Seal et al. (2022) uses survey data to show greater weight gain in adults with Stay-At-Home orders. Flanagan et al. (2021) shows that the Stay-At-Home orders resulted in improved diet quality in the short-term due to lower fast-food consumption.

This study has several distinct advantages over prior literature. Similar to Yang et al., we utilize geolocational datasets to estimate the effects of the Stay-At-Home orders. However, rather than daily evaluations for a subset of counties, we evaluate week-over-week trends in visits at the census tract-level for the whole United States. Geolocational datasets also provide distinct advantages over prior survey-based studies. The *Patterns* dataset from Safegraph captures the behavior of millions of people in a nationally representative panel, providing a more comprehensive sample compared to other research relying on more granular survey data. Lastly, our data allow insights into the long-term effects of the policy over time as we evaluate both the short-term and longer-lasting effect of the Stay-At-Home policies. This empirical approach will help highlight the long-term habit formation that started during the time of the Stay-At-Home orders during the COVID-19 pandemic.

1.2. COVID-19 and Access to Food

COVID-19 mitigation strategies included both mobility restrictions and business closures, changing both where and how food was purchased and consumed. First, in the week after declaring a state of emergency, all 50 states closed indoor dining at restaurants. Though some restaurants quickly shifted into take-out mode, many reduced opening hours and even closed during this period. The closure of indoor dining prevented many restaurants from operating at full capacity, either closing their service altogether, or curtailing the volume of orders. At the same time, fast-food restaurants were well-positioned to substitute for dine-in restaurants as they are designed around take-out mode of access. This may have resulted in substitution away from restaurant meals towards fast food and at home meals.

Second, in response to the COVID-19 pandemic, all 50 states declared a state of emergency, encouraging the shift to work-from-home when possible. A shift in employment meant a shift in consumption patterns for those who typically consume breakfast and lunch outside of their homes. In particular, the stay-at-home orders included closures of school cafeterias, forcing the venue of food consumption into homes for students and teachers, as well.

Combined, these policies imposed an exogenous shock to the venue and type of food consumption. The change in venue of school and work disrupted established food consumption routines as individuals substituted away from fast-food consumption towards at-home meals. The closure of indoor dining prevented many restaurants from operating at full capacity, either closing their service altogether, or curtailing the volume of orders.

COVID-19 mitigation measures upended many daily routine activities. Among these, food access was prominent, as limitations on people's mobility combined with business closures changed both where and how food was purchased and consumed. While the analysis in this paper focused on the Stay-At-Home orders which went into effect in 39 states and DC in March 2020, many policies affected where food was purchased and how it was consumed.

2. Data

To assess the impact of COVID-19 stay-at-home orders on food consumption behaviors, we employ a quasi-experimental approach using a difference-in-differences (DiD) model. This method allows us to compare changes in food venue visits across census tracts in states with and without stay-at-home orders, controlling for pre-existing trends. While, ideally, we would utilize granular purchasing data, these data are not readily available. Instead, we rely on high-frequency geolocation data to track mobility patterns and supplement this with state-level spending data to validate behavioral shifts. While these proxies do not directly measure food consumption, they provide valuable insights into consumer behavior and allow us to approximate broad shifts in habits over time

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2.1 Safe Graph Patterns: Mobility Data on Food Venue Visits

Our primary results use data from the SafeGraph *Patterns* platform, which tracks weekly foot traffic data from points of interest (POIs) across the United States starting from January 2019. The SafeGraph dataset consists of high-resolution cellular device data that tracks the geolocation of users of over 1,000 apps and links their movement to specific commercial establishments across space and time. The data contain information on the POI location name, address, North American Industry Classification System (NAICS) code, brand association, and business descriptor categories. In addition to the total visits to an establishment, the data also provide the census tract of origin of the visitors. We take advantage of this feature to re-organize the data around census tracts, tracking visits to types of establishments from each census tract.[1] We then restrict data to establishments by type, and count the number of visitors from every census tract at the weekly frequency. We define the establishments as the following: grocery includes as supermarkets and grocery stores (NAICS 445110, 452311); fast-food are defined as establishments which serve food without full service (NAICS 722513, 722514, 722515)[2], dine-in restaurants are defined as full-service restaurants (NAICS 722511). The Patterns dataset is aggregated to the customers' census tract of origin, not the location of the POI a customer visits.

The SafeGraph database has a few limitations. First, not every cellular device is tracked in this data, potentially creating selection bias among the devices that are tracked. To test the extent of such bias, SafeGraph has explored this potential selection by comparing education and household income of tracked devices to those in the American Community Survey at the state, census tract level, and census block group level. Their analysis finds high correlation at smaller geographic units. The high correlation weakens at the state level implying that the sample of users in the data is representative of the population at the census block group level.[3] Second, the SafeGraph data is not a comprehensive count of visitors to any given location as, in addition to tracking only a sample of cellular device users, it does not track individuals without such devices. We address this limitation by looking at the change in the volume of visits throughout the period of analysis, rather than the number of visits.

Furthermore, visits do not represent consumption. First, *Patterns* does not allow for measurement of the impact of online purchasing – services such as DoorDash, UberEats, Shipt which became more prominent during the pandemic. In an attempt to investigate this effect, we stratify to rural communities, where these services are less prominently available. Second, the data only represents visits, not expenditures, so we do not know what was purchased, much less consumed. We mitigate the effect of this shortcoming by confirming our results using limited expenditure data in SafeGraph's *Spend* dataset for establishments by type.

2.2. Safe Graph's Spend: Consumer Expenditures at Food Establishments

To validate our findings from the mobility data, we use the SafeGraph Spend dataset, which aggregates anonymized debit and credit card transactions from over 10 million consumers across more than 1 million food establishments. In addition to in-person sales, this data includes expenditures with purchase intermediaries (such as DoorDash, UberEats, or Shipt), furthering the investigation for delivery sales as well. Unlike the Patterns dataset, which is available at the census tract-week level, the Spend dataset is aggregated at the state-month level from January 2020 to December 2021. Despite this lower granularity, it provides valuable insights into how consumer expenditures evolved over time.

Similarly to SafeGraph's Patterns dataset, the Spend data is classified by NAICS code and we classify our categories, *fast-food, grocery,* and *restaurant,* in the same way. From here, we aggregate purchases from food vendors to create variable *total food*, representing any expenditure in total food consumption. Unlike the *Patterns* dataset, the *Spend* dataset cannot be cleanly aggregated at the weekly level or aggregated at the census tract-level. We aggregate expenditures by establishment types by the state-month level from January 2020 – December 2021. Despite the shorter timeline and less granular data than our main results, we believe the expenditure results, supplement the results from Safegraph's geolocational tracking data and present sufficient indication to how people are changing consumption behaviors following policy changes during the pandemic.

2.3. COVID-19 Policies

To track the implementation of policies, we use the COVID-19 US State Policy Database (CUSP).[4] While the data provide the precise date of implementation of stay-at-home policies, we choose the first week of March 2020 as the start of the treatment period. Though the implementation dates of stay-at-home orders differ across states, our data is organized at weekly frequency, which renders variability in implementation dates less important. We prefer to remain agnostic on the timing of treatment and instead choose the first week of March 2020 to capture the overall effect.

2.4 Stratification Datasets: Rurality & Food Access Research Atlas

To supplement our main findings, we conduct additional analysis stratified by grocery accessibility. Utilizing Food Access Research Atlas data, we define a census tract with *limited food access* as a census tract where the distance to the nearest grocery store is 1 mile away for urban census tracts and 10 miles away for rural census tracts. Additionally, we utilize this data to stratify census tracts by levels of enrollment in Supplemental Nutrition Assistance Program (SNAP). Our sample is divided by census tracts above the median SNAP usage in 2019 and those below the median SNAP usage in 2019.

In addition, we conduct stratifications by rurality of a census tract, median age, and employment levels. For rurality, we utilize the Census Bureau's TIGER (Topologically Integrated Geographic Encoding and Referencing System) mapping file for their geographic spatial data. This data classifies each census tract as either metropolitan, micropolitan, or rural, which we delineate into metropolitan and non-metropolitan.

3. Methodology

COVID-19 affected individuals' lifestyle in every state. However, states and county governments responded to the pandemic with different policies; in particular, some states implemented stay-at-home orders. We take advantage of this disparity in the implementation of stay-at-home orders to identify the impact of such sharp changes in mobility on choice of food outlet. Thus, we estimate a difference-in-differences specification comparing census tracts in states with stay-at-home orders to those without, before and after the first week of March 2020. Though lifestyle changed in every state after March 2020, our specification assumes that those with stay-at-home orders would have experienced a similar level of mobility as those without, and thus a comparison of these two groups allows for identification of the change in outcomes relative to the counterfactual as represented in states without stay-at-home orders. This specification relies on the assumption of conditional independence of assignment of treatment and presence of parallel pre-trends to simulate a quasi-random assignment of treatment and control.

Our baseline specification follows a two-way fixed effects difference-in-differences (DiD) model, where we estimate the impact of stay-at-home orders on weekly food venue visits at the census tract level. The model is specified as follows:

$$Y_{cst} = \alpha + \nu_s + \gamma_t + \beta_1 COVID_t * SaH_s + \epsilon_{cst} \quad (1)$$

where Y_{cst} are outcomes of interest, such as visits to food outlet by type for census tract *c*, state, *s*, in week *t.* The two-way fixed-effects are captured by ν_s, the indicator for each state, and γ_t an indicator for each week-year; the difference-in-differences are captured by $COVID_t$, SaH_s, $COVID_t * SaH_s$, and the relationship between the stay-at-home policy and outcomes of interest are captured by β_1. The two-way fixed effects account for state time-invariant characteristics, such as location of food outlets, and local culture about food; they also account for location invariant time characteristics, such as national events and policies. Standard errors, ϵ_{cst}, are clustered at state-level to account for serial correlation within treatment units.

To better understand the changes following the behavior shock during the COVID-19 pandemic, we split out "After" period into three subsections. Period 1 begins in March 2020 and continues until the final week of August 2020, the time when the Stay-At-Home orders were in place. During this time, mobility was most restricted, and many businesses, including restaurants, operated under limitations. Due to the ambiguity of the end of the Stay-At-Home periods, we generalize the closure at the end of the summer months of 2020. We define Period 2 as the end of August 2020 to end of December 2020. This represent the transition period after most stay-at-home orders were lifted but prior to COVID-19 vaccine distribution. Consumer behavior during this phase may reflect lingering caution rather than formal restrictions. Our final period is from January of 2021 until May of 2022 and represents the post-pandemic period following the vaccine rollout, allowing us to examine whether initial behavioral shifts persisted over the long run.

3.1 Potential Endogeneity

Although SafeGraph's data is representative at small geographic units, it does not track every single cellular device user, much less the entire population. As a result, we rely on changes in share, rather than levels, of visits across time and space. Our outcome variables, Y_{ct}, therefore, are defined using two measures: first, we use the ratio of visits to a food outlet type over total visits to all food outlets – in other words, $\frac{f_{ict}}{f_{FFct}+f_{Gct}+f_{Rct}}$ where f_{ict} is number of visits to fast-food (FF), grocery (G), or restaurant (R), over the sum of all visits to all three types of establishments; second, we define the log of visits to each type of establishment to allow for interpretation of results in terms of percent change.

Additionally, many restaurants and grocery stores closed permanently during the COVID-19 pandemic. These closures may have even been caused, in part, by the stay-at-home orders. However, due to the data being aggregated at the census tract of origin for each customer, customers' altering their consumption between different restaurants of the same establishment type will not alter the number of visits for that census tract. While restaurant closures may impact on the food landscape and availability of outlets, we are primarily concerned with whether individuals were motivated to change their visits to another open location of a similar establishment type, a different type of establishment, or to eliminate the mobility altogether.

3.2 Sensitivity and Robustness Checks

To ascertain the causal interpretation of our results, we must establish that prior to March 2020, the states in the treatment and control groups did not experience changes which could have explained trends seen after the implementation of stay-at-home orders, thus negating the relevance of these policies. To do so, we estimate an event study model of the following specification:

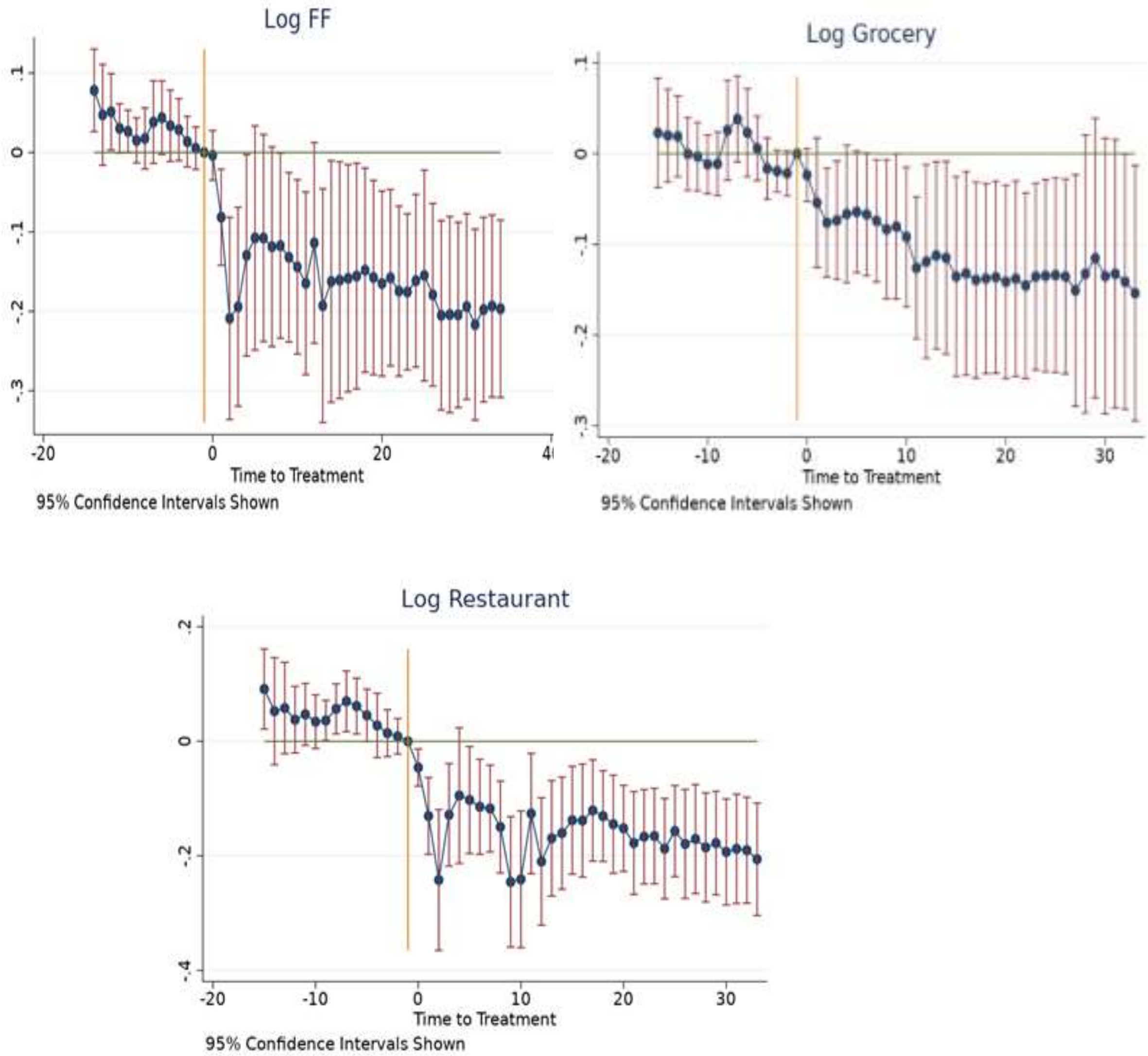
$$Y_{ct} = \alpha + \nu_c + \gamma_t + \sum_{t=1}^{T} \beta_{1t} \tau_t * SaH_c + \epsilon_{ct} \quad (2)$$

where Y_{ct}, ν_c, γ_t are defined as before. However, instead of an indicator for post-March 2020 period, each week-year is defined through a separate interaction $\tau_t * SaH_c$ with implementation of stay-at-home policy in census tract, *c.* Therefore, the array of coefficients β_{1t}, for each *t,* capture the weekly difference between states with and without stay-at-home orders, relative to a comparison omitted period, which we define the last week before March 2020. Our event study figures are reported as Figure 2 and Figure 3 in the Appendix. Finally, we stratify census tracts by geographic and demographic characteristics to evince heterogeneity in policy effect.

4. Results

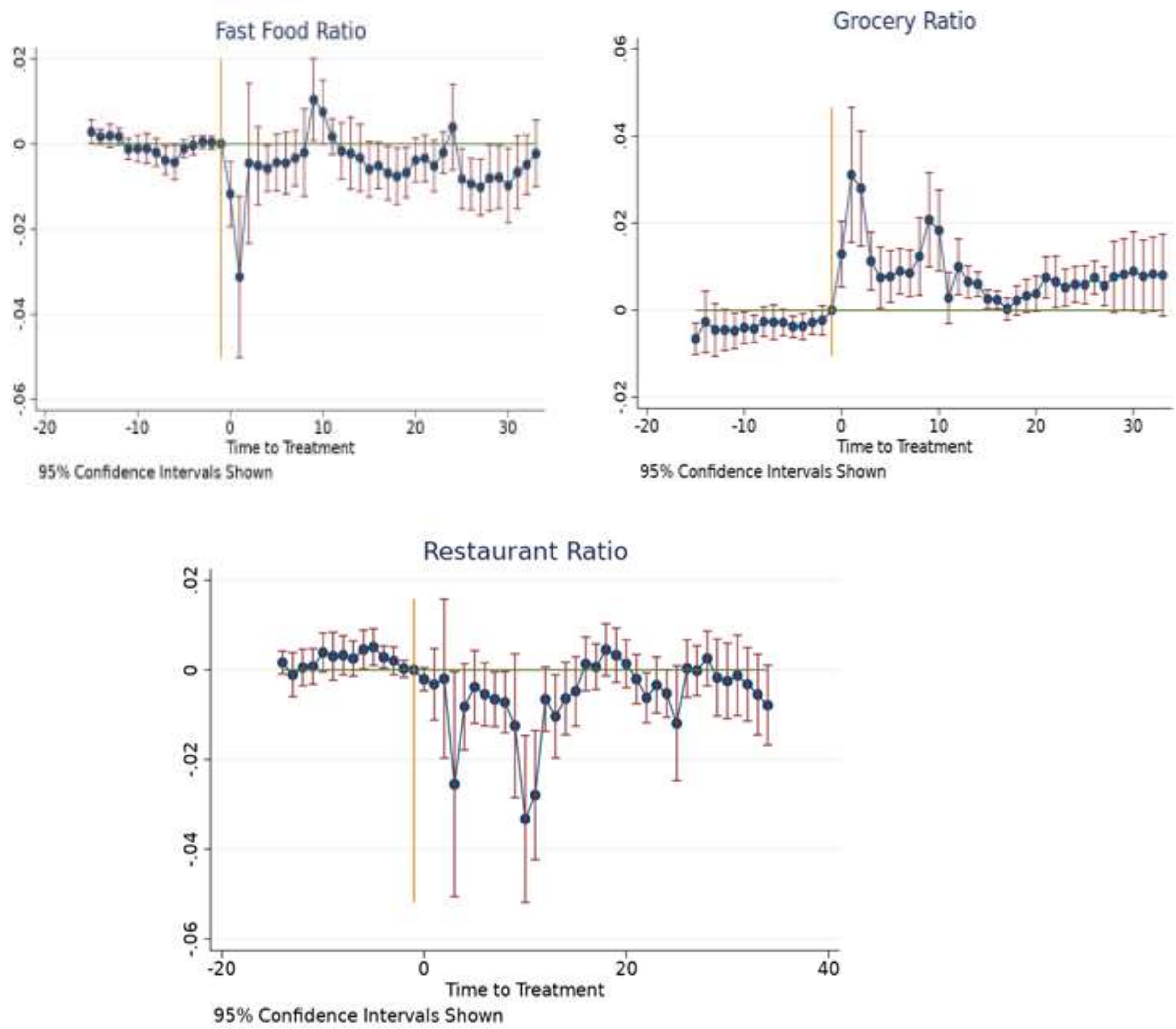
4.1 Overall Changes in Food Venue Visits

Our analysis indicates that COVID-19 stay-at-home orders led to significant and lasting reductions in visits to food venues, with the most prominent declines observed in fast-food and sit-down restaurant visits. From Table 1, immediately following the implementation of these policies (Period 1), visits to all food venues declined, with the largest reductions observed on fast-food and sit-down restaurant visits. At the census tract level, fast-food visits decreased by 19.8%, while sit-down restaurant visits declined by 18.3%. Grocery store visits also saw a smaller decline of 5.7%, suggesting a shift toward food-at-home consumption. These effects persisted beyond the initial lockdown period (Period 2 & 3), with evidence that consumer mobility remained lower than pre-pandemic levels even after restrictions were lifted.



Source: SafeGraph *Patterns*. Each graph is a separate specification. Outcomes are logged changes in visits to fast-food, grocery, and restaurants. Panel A is the logged number of fast-food visits, Panel B is the logged number of grocery store visits, Panel C is the logged number of restaurant visits. Specifications also control for census tract and month-year fixed effects. Standard errors are clustered at the state level. Time 0 represents March 2020.

Figure 2.Difference-in-differences in the Logged Number of Visits by Type Adjusted for Location and Seasonal Trends in A Monthly Event Study Format.



Source: SafeGraph *Patterns*. Each graph is a separate specification. Outcomes are logged changes in visits to fast-food, grocery, and restaurants. Panel A is the ratio of fast-food visits, Panel B is the ratio of grocery store visits, Panel C is the ratio of restaurant visits. Specifications also control for census tract and month-year fixed effects. Standard errors are clustered at the state level. Month 0 represents March 2020.

Figure 3. Difference-in-differences in the Ratio of Visits by Type Adjusted for Location and Seasonal Trends in A Monthly Event Study Format.

Table 1. Difference-in-Differences in The Log of Visits by Type Adjusted for Location and Seasonal Trends.

	(1)	(2)	(3)
	Log Fast-Food Visits	Log Grocery Visits	Log Restaurant Visits
March - August 2020	-0.198*** (0.059)	-0.057* (0.034)	-0.183*** (0.044)
August - December 2020	-0.150** (0.071)	-0.076* (0.042)	-0.158** (0.071)
January 2021 - May 2022	-0.196*** (0.065)	-0.131** (0.061)	-0.210*** (0.064)
Observations	15,249,476	15,249,476	15,249,476
R-squared	0.886	0.797	0.885

Source: SafeGraph *Patterns*. Each column is a separate specification. Specifications also control the census tract and week-year fixed effects. The dependent variables are the logged number of reported visits for fast-food, grocery, and restaurant. Standard errors are clustered at the state level and reported in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

4.2 Changes in the Share of Food Venue Visits

In Table 2, relative to the total sum of all visits, we see a 4.4% decrease in the share of fast-food and a statistically insignificant 2.6% decrease in the share of sit-down restaurant visits substituted for a 19.4% increase in the share of grocery store visits in the initial period following the implementation of the Stay-At-Home orders. These changes do not appear to last indefinitely. In each period, the ratio of total visits to each establishment moves closer to the pre-pandemic levels. Although, as indicated in Table 1, the overall levels of visitation to each establishment decreased significantly and lastingly at the onset of the Stay-At-Home orders, the share of visits to each establishment has moved back towards pre-policy levels. The combination of results in Table 1 and Table 2 indicate that the overall levels of mobility have decreased significantly, indicating that consumers in Stay-At-Home states have made a long-term shift in their overall mobility when it comes to food options, but have not made lasting, significant changes to their preferences about where.

Table 2. Difference-in-differences in the ratio of visits by type adjusted for location and seasonal trends.

	(1)	(2)	(3)
	Fast Food Ratio	Grocery Ratio	Restaurant Ratio
March - August 2020	-0.017** (0.007)	0.029*** (0.007)	-0.012 (0.007)
August - December 2020	-0.005 (0.003)	0.013*** (0.005)	-0.009** (0.004)
January 2021 - May 2022	-0.003 (0.002)	0.011*** (0.002)	-0.008*** (0.003)
Observations	15,249,476	15,249,476	15,249,476
R-squared	0.589	0.554	0.584
Y-Mean	0.383	0.149	0.468

Source: SafeGraph *Patterns*. Each column is a separate specification. Specifications also control the census tract and week-year fixed effects. The dependent variables are the ratio of visits of total sum of fast-food, grocery, and restaurant. Standard errors are clustered at the state level and reported in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

4.3 Changes in Consumer Spending

One limitation of using a geo-locational dataset is that there is no indication about the amount of money that is spent at any of these locations. It is possible that consumers chose to reduce their risk of infection from the COVID-19 virus by opting for fewer visits and purchasing higher quantity at each visit. Thus, consumers would not be changing their food consumption habits, only the number of trips to food outlets. Another possible limitation is that many of the visitors are drivers for a delivery service, such as GrubHub or UberEats, and are making deliveries outside of the driver's census tract.

"Given the limitations in the geo-locational data, we conducted a robustness check using SafeGraph's Spend dataset to explore whether changes in mobility were accompanied by changes in spending behavior. As mentioned above, the Spend dataset includes the same identification for each POI and each column can be understood to be the same type of establishment as in prior tables. However, this data cannot be aggregated to the census tract or week levels and is instead reported at the state-month level in Table 3.

Table 3. Difference-in-differences in the Ratio of Spending and Logged Spending by Type Adjusted for Location and Seasonal Trends.

	(1)	(2)	(3)	(4)	(5)	(6)
	Fast Food Ratio	Grocery Ratio	Restaurant Ratio	Log Fast-Food Spending	Log Grocery Spending	Log Restaurant Spending
March - August 2020	-0.020*** (0.006)	0.012*** (0.004)	0.008 (0.005)	-0.080*** (0.029)	-0.001 (0.018)	-0.200*** (0.066)
August - December 2020	-0.016*** (0.006)	0.015*** (0.004)	0.002 (0.004)	-0.059 (0.041)	0.003 (0.037)	-0.190** (0.087)
January 2021 - May 2022	-0.011 (0.008)	0.005 (0.007)	0.006** (0.002)	-0.240 (0.220)	-0.204 (0.208)	-0.247 (0.213)
Observations	1,377	1,377	1,377	1,377	1,377	1,377
R-squared	0.951	0.972	0.922	0.967	0.975	0.972
Y-Mean	0.327	0.594	0.0791			

Source: SafeGraph *Spend*. Each graph is a separate specification. Outcomes are logged changes in visits to fast-food, grocery, and restaurants at the state-month level. Columns 1, 2, and 3 represent the changes in the ratio of visits to fast food, grocery, and restaurants. Columns 4, 5, and 6 represent the logged number of fast-food visits, grocery store visits, and restaurant visits. Specifications also control for state and month-year fixed effects. Standard errors are clustered at the state level and reported in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

Similarly to our results from Table 2, which reports investigating the share of spending, we find in Table 3 (Columns 4, 5, and 6) that the share of total food expenditures spent at the grocery store also increased slightly in Stay-At-Home states following the implementation of the Stay-At-Home orders. Primarily, this change from fast-food and into grocery stores, but this change did not continue past December 2020 (Period 2). In terms of logged spending (Columns 1, 2, and 3), we again see decreases in spending at fast-food restaurants (-8%) and sit-down restaurants (-20%) following the implementation of the Stay-At-Home orders. Meanwhile, the grocery store spending does not appear sensitive to Stay-At-Home orders. However, unlike our mobility results, we do not see statistically significant, long-lasting effects. In terms of overall spending levels, we conclude no evidence of statistically significant decreases in the long run (Period 3). These results further indicate that the preferences and spending of the consumers have not changed but instead our mobility results are capturing changes in how consumers acquire food. The consistency between the visits and spending in the early period following the pandemic confirms our belief that these orders initially resulted in a substitution away from fast-food and restaurant consumption and towards at-home consumption.

Table 4. Difference-in-differences in the Ratio of Visits and Logged Visits by Type Adjusted for Location and Seasonal Trends.

Panel A:	Rural & Micropolitan			Metropolitan		
	(1)	(2)	(3)	(4)	(5)	(6)
	Fast Food Ratio	Grocery Ratio	Restaurant Ratio	Fast Food Ratio	Grocery Ratio	Restaurant Ratio
March - August 2020	-0.004 (0.007)	0.017** (0.008)	-0.013* (0.007)	-0.018*** (0.006)	0.031*** (0.007)	-0.013* (0.007)
August - December 2020	-0.002 (0.004)	0.007** (0.003)	-0.006 (0.005)	-0.005 (0.004)	0.013*** (0.004)	-0.008* (0.004)
January 2021 - May 2022	0.003 (0.003)	0.004** (0.002)	-0.007* (0.004)	-0.004* (0.002)	0.012*** (0.002)	-0.008*** (0.003)
Observations	2,475,184	2,475,184	2,475,184	12,677,602	12,677,602	12,677,602
R-squared	0.610	0.606	0.528	0.543	0.493	0.556
Y-Mean	0.423	0.148	0.429	0.376	0.147	0.477
Panel B:	Rural & Micropolitan			Metropolitan		
	(1)	(2)	(3)	(4)	(5)	(6)
	Log Fast-Food Visits	Log Grocery Visits	Log Restaurant Visits	Log Fast-food Visits	Log Grocery Visits	Log Restaurant Visits
March - August 2020	-0.054* (0.031)	-0.027 (0.023)	-0.093** (0.043)	-0.188*** (0.054)	-0.036 (0.028)	-0.179*** (0.044)
August - December 2020	-0.034 (0.029)	-0.010 (0.023)	-0.051 (0.035)	-0.128** (0.061)	-0.049 (0.032)	-0.135** (0.061)
January 2021 - May 2022	-0.051* (0.030)	-0.051 (0.040)	-0.083** (0.033)	-0.174*** (0.054)	-0.082* (0.043)	-0.188*** (0.054)
Observations	2,463,810	2,432,243	2,468,024	12,627,958	12,493,849	12,652,116
R-squared	0.913	0.802	0.889	0.877	0.795	0.876

Source: SafeGraph's Patterns. Specifications also control for census tract and week-year fixed effects. Metropolitan counties are defined by the Census's TIGER file. The dependent variables in Panel A are the ratio of visits of total sum of fast-food, grocery, and restaurant. The dependent variables in are a log transformation of visits by type of food outlet. Standard errors are clustered at the state level and reported in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

4.4 Metropolitan & Non-metropolitan Census Tracts

To investigate the underlying heterogeneity of our results, we perform a myriad of stratifications to better understand the breadth of the changes. First, in Table 4, we separate our samples according to Census's TIGER shape file to classify all census tracts as metropolitan census tracts or rural and urban census tracts. Panel A reports the DiD coefficient for the ratio of total food visits by establishment type. The resulting changes from the Stay-At-Home policy are similar in direction between the metropolitan and the non-metropolitan census tracts. However, the rural and micropolitan census tracts appear to have experienced less disruption (0.8% decrease to fast-food, 11.5% increase to grocery, 3% decrease to restaurants) in the relative share of their total visits at the onset (Period 1) than the metropolitan census tracts (4.8% decrease in fast-food, 21.1% increase to grocery, and 2.7% increase to restaurants). Although all the effects moved directionally back towards 0 (pre-pandemic levels), the difference between metropolitan census tracts (0.7% decrease in fast-food, 2.7% increase in grocery, and 1.6% decrease in restaurants) and non-metropolitan census tracts (1.1% decrease in fast-food, 8.2% increase in grocery, and 1.7% decrease in restaurants) remained.

Panel B reports the logged changes in visits by establishment type for both subsets of our sample. Although the reported directions are all directionally the same (decreasing in visits), we can see differences in the magnitude of the effect sizes between the metropolitan census tracts and non-metropolitan census tracts. For each establishment type and in each period, the percentage decreases in visits for metropolitan census are comparatively larger. We find that the directional effects of the stay-at-home order on food venue choices are consistent regardless of rurality, though the magnitude diminishes with the less populated census tracts. This largely aligns with the literature by Callaghan et al. 2021, suggesting that rural households were less likely to adhere to COVID policies experienced less of a routine shock than their urban contemporaries. Interestingly, although the effect sizes are smaller for the more rural and micropolitan census tracts in each period, the magnitude of the effect sizes persistent at the same level throughout the entirety of the study. This once again suggests that the change in relative mobility remained even following the closure of the Stay-At-Home orders and the end of the COVID-19 pandemic.

Census Tracts with Poor Food Access

Lastly, we investigate heterogenous effects by census tracts with low access to grocery stores. This analysis will indicate if households with higher barriers to grocery store visits experienced similar changes to those with easier access. We define low access census tracts by the census tract's distance from a grocery store: 10 miles for a rural census tract and 1 mile for an urban census tract. Urban and rural tracts are defined by data purveyors, the Food Access Research Atlas. The results of this analysis are reported in Table 5.

Table 5. Difference-in-differences in the Ratio of Visits and Logged Visits by Type Adjusted for Location and Seasonal Trends.

Panel A:	Low Food Access Census Tracts			High Food Access Census Tracts		
	(1)	(2)	(3)	(4)	(5)	(6)
	Fast Food Ratio	Grocery Ratio	Restaurant Ratio	Fast Food Ratio	Grocery Ratio	Restaurant Ratio
March - August 2020	-0.009 (0.006)	0.030*** (0.008)	-0.021** (0.008)	-0.015** (0.006)	0.030*** (0.009)	-0.015 (0.009)
August - December 2020	-0.000 (0.003)	0.011*** (0.004)	-0.011** (0.005)	-0.002 (0.003)	0.013*** (0.004)	-0.011** (0.004)
January 2021 - May 2022	-0.001 (0.002)	0.010*** (0.002)	-0.009*** (0.003)	-0.004 (0.003)	0.011*** (0.003)	-0.008* (0.004)
Observations	5,757,323	5,757,323	5,757,323	10,580,207	10,580,207	10,580,207
R-squared	0.620	0.594	0.592	0.568	0.532	0.587
Y-Mean	0.396	0.145	0.459	0.376	0.153	0.470
Panel B:	Low Food Access Census Tracts			High Food Access Census Tracts		
	(1)	(2)	(3)	(4)	(5)	(6)
	Log Fast-food Visits	Log Grocery Visits	Log Restaurant Visits	Log Fast-food Visits	Log Grocery Visits	Log Restaurant Visits
March - August 2020	-0.138*** (0.048)	-0.023 (0.025)	-0.176*** (0.052)	-0.218*** (0.066)	-0.069* (0.037)	-0.216*** (0.060)
August - December 2020	-0.074 (0.055)	-0.030 (0.032)	-0.103* (0.057)	-0.150** (0.072)	-0.083* (0.045)	-0.170** (0.071)
January 2021 - May 2022	-0.128** (0.050)	-0.079 (0.050)	-0.155*** (0.051)	-0.214*** (0.071)	-0.147** (0.063)	-0.227*** (0.068)
Observations	5,757,323	5,757,323	5,757,323	10,580,207	10,580,207	10,580,207
R-squared	0.902	0.820	0.900	0.874	0.788	0.878

Source: SafeGraph's *Patterns*. Specifications also control for Census Tract and week-year fixed effects. Low Food Access is defined by a census tract's distance from a grocery store: 10 miles for a rural census tract and 1 mile for an urban census tract. The dependent variables in Panel A are the ratio of visits of total sum of fast-food, grocery, and restaurant. The dependent variables in are a log transformation of visits by type of food outlet. Standard errors are clustered at the state level and reported in parenthesis. * p<0.1, ** p<0.05, *** p<0.01.

In Panel A of Table 5, we report the changes in the share of the visits to each establishment. The changes in share of visits to the grocery store and restaurants are nearly identical for each period for both low and high access census tracts. At the conventional 5% level, there is no statistically significant change in the share of visits to fast-food for census tracts with low food-access but a 4% decrease for the share of visits for high census tracts. However, in all subsequent periods, there is no statistically significant change in the share of visits to fast food establishments for either low or high access census tracts. As a share of overall visits, there appears to be no heterogeneity in the effects of the Stay-At-Home orders due to levels of food access.

In Panel B of Table 5, we report the effects of the overall change of visits following the stay-at-home orders. The effects were most pronounced in the census tracts deemed to have adequate food access. In the initial period, for fast food (-13.8% for low access, -21.8% for high access), grocery (no statistically significant change for low access, -6.9% for high access, and restaurants (-17.6% for low access, -21.6% for high access), the census tracts with better food access experienced more disruption. This difference remained in each period and to each establishment type. Low access census tracts had less disruption in visits than the high access census tracts. The magnitude of the long-term changes indicated in Period 3 match similarly to the changes in Period 1 for both groups, which serves as evidence that the long-term behavior has changed.

5. Discussion

The study results reveal significant changes in consumer behavior regarding food venue visitation following the implementation of Stay-At-Home orders in various states. Notably, our findings indicate a substantial decline in visits to fast-food outlets, grocery stores, and sit-down restaurants at the census tract level during the initial period after the enforcement of these orders. Specifically, we observed a 19.8% decrease in fast-food visitation, a 5.7% decline in grocery store visitation, and an 18.3% reduction in restaurant visitation.

This decline in mobility for the census tracts receiving the Stay-At-Home orders persisted throughout the COVID-19 pandemic, the closure of the orders, and even after the introduction of the COVID vaccine. As illustrated by the logged results in Table 1, the overall levels of visitation decreased significantly at the onset of the orders and continued to remain below pre-pandemic levels throughout the remainder of the study. However, the share of visits (Table 2) to each establishment gradually has returned to pre-pandemic levels over time. This makes evident that while consumers in Stay-At-Home states made long-term adjustments in their overall mobility regarding food options, their preferences regarding where to purchase food did not change.

Furthermore, our stratification analysis revealed interesting insights regarding the persistence of the effects of Stay-At-Home orders and the effects on different demographic groups. While both metropolitan and non-metropolitan areas experienced declines in visitation, the magnitude of these effects varied. Metropolitan census tracts had a much steeper decline in overall food visits following the implementation of the Stay-At-Home orders than their more rural counterpart.

Our analysis of census tracts with low access to grocery stores showed nearly the exact same changes in visitation patterns to those with superior access. This suggests that the effects of Stay-At-Home orders on food venue choices were not significantly influenced by the proximity to grocery stores but the census tracts with lower food access did not have as sharp of a decline in overall visits. It is possible that census tracts with better food access make more frequent visits to these establishments and therefore reduced to less frequent shopping. However, due to the restrictions on the data discussed earlier, we are unable to examine this question.

While these findings provide valuable insights into shifts in consumer mobility, several limitations must be acknowledged when interpreting the results. A key limitation of our study is the inability to track consumer spending patterns directly. Although Safegraph's Patterns dataset provides data on where consumers go, we do not know what or how much these consumers spent at these locations. We also acknowledge that the increased role of delivery services a likely affecting visitation patterns. To address these limitations, we conducted a robustness check using spending data from SafeGraph's Spend dataset. While the SafeGraph Spend dataset provided some insight, it is available only at the state level, which introduces potential biases, especially for areas where Stay-At-Home orders were implemented at the county level. While the less granular Spend results broadly follow the pattern of our initial findings regarding changes in visitation patterns, we acknowledge that both datasets are imperfect.

While this study focuses on the impact of Stay-At-Home orders, it is important to recognize that these orders were one of many public health policies implemented during the pandemic. The complexity of these overlapping policies means that isolating the specific effects of Stay-At-Home orders on food acquisition behavior is challenging. Despite the presence of multiple public health policies during the pandemic, the Stay-At-Home orders provide a distinct examination given their direct impact on mobility, allowing for a focused analysis of shifts in consumer behavior in response to these specific restrictions.

Despite these challenges, our findings offer a useful lens into the lasting impact of pandemic-era policies on consumer behavior. In this study, a notable finding emerged regarding the impact of Stay-At-Home orders on food choices: the initial effect persisted even after the return to post-pandemic life. The extent of these long-term changes consistently correlated with the magnitude of changes observed during the initial period, irrespective of factors such as rurality, food access, or economic indicators. These findings suggest significant and long-term changes within the food sector, indicating a need for further examination and adaptation of public policy to evolving consumer preferences.

Moving forward, further research is warranted to explore the long-term impacts of the pandemic-era policies, particularly in terms of food choices and consumption habits. Given the substitution between away-from-home consumption (fast-food or restaurants) to in-home consumption, it is important to decipher if this is an improvement in consumers' diet quality. In general, a reduction in restaurant and fast-food consumption constitutes an improvement in dietary quality and is associated with fewer calories (An, 2016; Saksena et al., 2018). However, little work has been done about the nutritional quality and caloric count of food consumed at home throughout the pandemic. Are consumers purchasing more low-quality foods or are consumers eating healthier than pre-pandemic? Work by Flanagan et al., (2021) suggests that the decrease in away-from-home consumption improved overall diet quality during the onset of the pandemic. Utilizing product-level transaction data could shed light on the types of food and the nutritional quality of purchases for households with restricted mobility.

With the rise of food platforms such as meal delivery apps and online grocery services, future researchers should explore their role in shaping consumer behavior and dietary choices. Considering research that shows calorie labeling has encouraged healthier levels of consumption (Shangguan et al., 2019), it is important to ensure that similar labeling is present in digital platforms and that the labelling has the same effect both in-person and in-app. A bulk of the strategies for promoting healthier consumption in retail settings is oriented around in-person consumption strategies (Wolgast et al., 2022). Understanding the impact of these platforms on food access, affordability, and nutritional quality is critical for informing future policy decisions. Given this study and other's results show persistent changes in consumer behavior following the COVID-19 pandemic, policymakers should prioritize long-term understanding for consumer behavior in the food sector.

In conclusion, this study highlights the enduring effects of Stay-At-Home orders on food venue choices, suggesting that even after the return to post-pandemic life, consumer behavior in the food sector has been altered. Understanding these shifts, especially in the context of emerging food delivery platforms and changing consumption patterns, is critical for informing future policies aimed at promoting healthier food environments.

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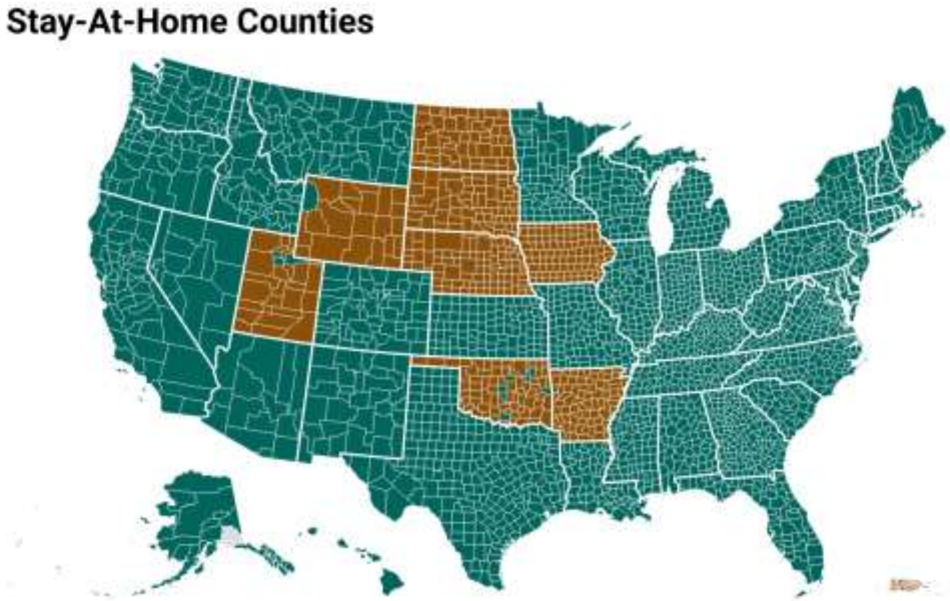
Figure 1: Map of Stay-At-Home Counties



Source: *CUSP*. Created with DataWrapper. Orange counties refer to the counties that did not implement stay-at-home orders during the COVID-19 pandemic, while green counties represent counties that implemented stay-at-home orders.

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[1] *SafeGraph* censors observations of fewer than 3 visitors to establishments, resulting in undercounting of visitors from some census tracts.
[2] This includes limited-service restaurants (delis, pizza shops, fast-food restaurants, fast casual restaurants, takeout eating places, etc.), cafeterias / buffets (self-serve eating establishments such as Fuddruckers), snack and non-alcoholic beverage bars (doughnut shops, bagel shops, coffee shops, ice cream parlors, etc.).
[3] More detail on SafeGraph analysis can be found at: https://www.safegraph.com/blog/what-about-bias-in-the-safegraph-dataset.
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