Public Transportation Access and Food Insecurity

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Abstract

Public transportation networks connect poor urban households in food deserts to grocery options and nutritious food. This paper examines how the exit of public transit options in an urban food desert affects a household's access to and utilization of grocery stores over drug and dollar stores, as well as the healthfulness of the foods these households purchase. I contribute an original data set of all transportation network changes across 138 cities in the U.S. over the period 2008-2019. I combine this with UPC codes of all consumer packaged goods bought by tens of thousands of urban households over the same period. The exit of public transportation options in an urban food desert is associated with a significant decrease in the number of yearly trips households make to grocery stores and an increase in the number of yearly trips made to drug and dollar stores. Further, households that experience such an exit subsequently buy fewer healthy foods and more unhealthy foods. The results from this research suggest that maintaining public transit infrastructure is an important public policy concern and that cuts to public transit networks directly impact urban households' access to nutritious food.

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1 Introduction

Across the country, families in urban food deserts struggle to access healthy food without cars. In Newark, New Jersey, individuals in urban food deserts report traveling two miles or more, without a car, to access food. They rely on a combination of bus lines, taxis, and friends and family to get them to food and devote their infrequent days off to procuring food for their families (ABCNews (2022)). In Fresno, California, residents of a mobile home park live half a mile from a grocery store but have no way to access it by foot without crossing a busy street. A free bus line gave these households safe and immediate access to a grocery store (ABC30 (2022)).

Low-income communities disproportionately face inferior access to healthful food. “Food deserts” in urban areas are defined as neighborhoods where a significant share of residents have to travel over one mile to access a grocery store, and affect over 17 million Americans (USDA (2015)). Households without immediate access to a grocery store rely on drug, dollar and convenience stores or must travel long distances for food. 60% of urban neighborhoods where the median household income is below 1.5 times the poverty line have one or fewer bus stops, and half of such neighborhoods have no transit stops at all (Bureau (2021)). Households in neighborhoods with low access to transportation may find themselves trapped in consumer markets. Without good quality access to transit, and with the high fixed cost of buying a car, these households may be limited to stores that are within walking distance from their homes. Low-income and minority households rely on public transportation more heavily than high-income and white households. SNAP-participating and food-insecure households are less likely to drive their own car to do their primary food shopping and more likely to get rides from someone else or walk, bike, or take public transit. Only 66% of SNAP participating households use their own car to access a grocery store, while 95% of higher income households do so (USDA (2015)). Households in neighborhoods without immediate access to a grocery store rely on drug and convenience stores for their shopping. Further, low-income households are less likely to own a car, and therefore rely much more heavily on public transportation than their wealthier counterparts (Giuliano (2017)).

Using a large, original data set of all the transit routes, trips and stops for 138 cities throughout the country and how they change over time, as well as UPC data of the purchases of tens of thousands of households, I exploit the haphazard and uneven removal of transit stops. I determine causally the importance of transportation access on the shopping habits and nutrition of urban households. To perform this analysis, I focus on households who live in neighborhoods that are urban food deserts with low transit access. Transit exit is defined as a zip code going from one or more stops to zero stops. I use a modern event-study design from Callaway and Sant'Anna (2021) with households that have not yet lost their transit options as the control group. Outcome variables include whether such households, when they have more limited transit access, change where they shop and the nutritional makeup of what they buy. I find that households decrease the number of trips they make to grocery stores and increase the number of trips they make to drug and dollar stores. Further, I study whether the nutritional makeup of households' purchases changes as a result using hand-coded data of over 1,400 food categories. I find a persistent decrease in the number of healthful products bought and an increase in the number of unhealthful products bought. I perform heterogeneity analysis across these outcomes and find that results are most significant for poor households. Finally, I study the entry of transit in urban neighborhoods, and find that there is no change in consumption patterns as a result. This paper is the first nationwide, causal study on the impact of public transportation networks on shopping habits and nutrition.

The organization of cities and public transit impact every aspect of urban life, including social networks (Bailey et al. (2020)), mental health (Leventhal and Brooks-Gunn (2003)), household income (Barton and Gibbons (2017)) labor market outcomes (Åslund et al. (2017) Blumenberg et al. (2015) Garasky et al. (2006)), and income segregation (LeRoy and Sonstelie (1983) Pathak et al. (2017) Akbar (2021)). Several studies exist that sketch the relationship between urban public transit and food. Baek (2016) finds that improvements to public transportation reduce food insecurity at the aggregate, city level. Fitzpatrick et al. (2016) and Allard et al. (2017) both find that areas with less public transit and fewer food retailers have a higher share of households reporting food insecurity, though these measures are correlative. My paper is uniquely situated in the literature as the first causal evidence of the effects of public transit access on food access and nutrition.

Allcott et al. (2019) uses grocery store entry into neighborhoods as a way to understand whether improved grocery access directly affects “nutritional inequality”, or the idea that poorer households have poorer nutrition. They find that exposing poor neighborhoods to the food options of wealthier neighborhoods closes the nutritional inequality gap by 9%. The authors suggest that because people generally do their grocery shopping by car, households are not impacted by grocery store entry in their neighborhood. This important paper relies heavily on rural areas with little food access, and leaves open the question of how urban neighborhoods, where few people own cars, respond to an increase in their food access via transportation. Additionally, urban consumption is found to be highly segregated in Davis et al. (2019); spatial and social frictions influence restaurant choices. Individuals are less likely to visit venues in neighborhoods demographically different from their own.

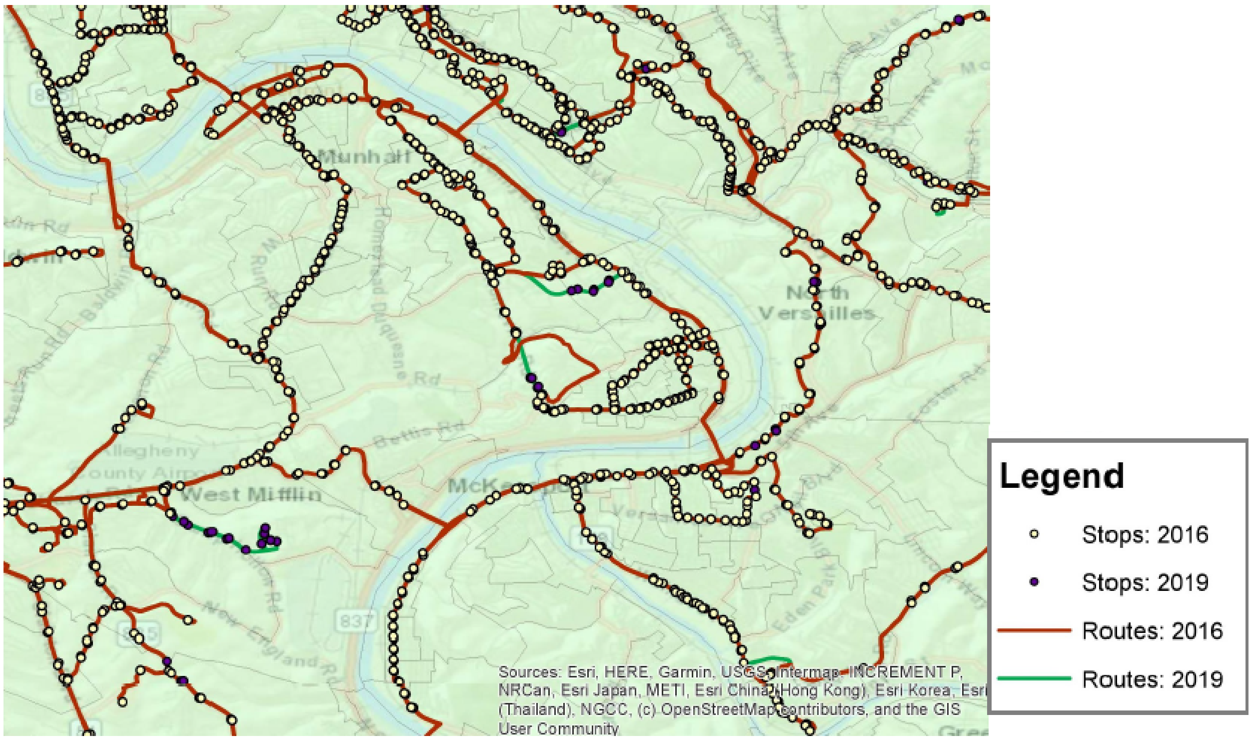
I make several important contributions to the literature. This is the first study to isolate the causal impact of transit on consumption patterns and nutrition. Additionally, I add to the work done by Allcott et al. by focusing on poor urban households who are disproportionately likely to rely on transit for groceries. Finally, I contribute an original dataset of the entire transit network for 138 cities in the U.S. and how they change over time.

2 Data

2.1 Public Transportation Data

I construct a unique dataset of all public transportation stops and routes over the years 2008-2019 for 138 metro areas across the U.S. These cities are shown in figure A.1. Public Transportation data is hosted on the open data service Transitland, which contains a directory of transit feeds organized in the General Transit Feed Specification (GTFS). GTFS defines a common format for public transportation schedules and their associated geographic information. This specification allows transportation agencies to publish their transit data in a format that can be consumed by a wide variety of software applications, including Google Maps. The GTFS contains a static component where each transit agency in the U.S. shares route, trip, and stop location data. Nearly every transit agency in the country adheres to the GTFS system, however, there is no national database of transportation agencies or stops. Community users of Transitland (2021) archive this data, which will allow me to exploit changes in transit networks, including when stops, as well as trip times and routes, appear and disappear across time. I focus on households that experience a change in transit access during this panel. Figure 1 presents an example of this on the south side of Pittsburgh.

Figure 1: Bus Routes and Stops, Pittsburgh 2016 vs 2019



The red lines and yellow dots represent the bus network in an area of Pittsburgh in 2016. The green lines and purple dots represent parts of the network that are new as of 2019. The neighborhood of West Mifflin, on the bottom left, gains new transportation access over this period, an example of the changes I exploit in this data. Neighborhoods are identified as having lost transportation access if there are no longer bus stops that appeared in a previous archived version of the data.

2.2 Nielsen Homescan

Individual consumer data comes from the Nielsen Homescan data set from the Kilts Center Chicago Booth (2021) for the years 2008-2019. This is a nationally representative panel that includes tens of thousands of households across the U.S. Households participating in this panel record UPCs of all consumer packaged goods they purchase from any outlet, which

I use to analyze what consumers buy and where they shop. Because households scan their purchases every time they shop, I trace routine habits including how frequently they shop, where they go, and what types of products they buy. Additionally, each year, participating households report demographics such as household composition, race, age, education and employment. The sample is limited to households in zip codes that do not contain a grocery store. A limitation of the Nielsen homescan is that it includes only packaged items with UPCs, meaning that households do not record the purchase of non-packaged items such as bulk produce and grains. The literature shows that about 60% of households' produce calories are from packaged goods that are observed in the homescan data, and this proportion does not vary significantly on observables (Allcott et al. (2019)).

Table 1: Household and Zip Code Summary Statistics

	Mean	Standard Deviation
Panel A: Nielsen Households		
Household Size	2.39	1.26
Household Income	20.32	5.96
White	0.86	034
Black	0.07	0.25
Hispanic	0.06	0.24
Non-Hispanic	0.94	0.24
Married	0.68	0.46
Single	0.13	0.34
Observations	17945	
Panel B: Zip Codes		
AGI	12219.01	14511.23
Population	6411.19	7682.69
White	.87	.16
Black	.06	.12
Observations	4925	

Summary statistics are at the household level in Panel A. The population is all households that do not have grocery stores in their zip code. Zip code summary statistics are in Panel B, and this is also the population of zip codes that do not have grocery stores. Zip code data comes from the 2017 5 year American Community Survey.

Panel A of Table 1 shows summary statistics for households that are in the sample, which is households in the 138 cities and in zip codes that do not have grocery stores. Panel B contains summary statistics for the relevant zip codes. Zip code level controls come from the 2017 American Community Survey 5 year data.

Table 2: Household Shopping Habits

	Mean Trips Per Year	Standard Deviation	Percent of Total
Grocery	56.11	21.49	41.93%
Discount	31.61	19.79	27.74%
Warehouse	12.64	10.97	5.90%
Drug	8.33	07.23	5.35%
Convenience	2.65	04.55	1.68%
Department	0.67	01.79	0.51%
Delivery	0.01	00.12	0.01%
Other	23.54		16.98%
Total	138.64		
Observations	82722		

Shopping habits per year for households in zip codes without grocery stores. Included are the eight most relevant categories. The grocery category includes superstores.

Nielsen breaks down store types into 66 categories, everything from grocery stores to party supply stores, camera stores, craft stores and fruit stands. The 8 most relevant categories are listed in Table 2, which summarizes the shopping habits of households in the sample. The categories are broad. Grocery includes super stores like Walmart. Discount stores in the U.S. are largely dollar stores.

2.3 Nutrition Data

The Nielsen Homescan data contains information on the foods and other products households are purchasing. They use several identifiers, including product module codes, which break products into 1,407 specific categories. This identifier is the level of aggregation above UPC codes that combines products by brand and size but keeps each type of product distinct. I label these product module codes as 'healthful' or 'unhealthful' (or neither, in the case of non-food items) using the 2010 *Dietary Guidelines for Americans* (DGA) from the

USDA. In this guideline, food groups are labeled as recommended for increased consumption (healthful) or recommended for limited consumption (unhealthful). These terms, healthful and unhealthful, are used for simplicity and are not intended to describe entire food groups, but rather to provide an overall idea of the healthfulness of a basket of consumer goods. Table A.1 in the appendix provides a picture of more general categories of foods in the Nielsen Homescan panel, product groups, and what fraction of goods in that category are considered healthful vs unhealthful. This data will be used to measure whether the overall healthfulness of consumers' purchases changes with the change in access to public transportation options. Grocery store location data comes from the USDA, and is used to exclude households in zip codes that contain a grocery store. Table A.2 shows that these zip codes are fundamentally different from those which have a grocery store. The final data set is composed of all households that do not have grocery stores in their zip code and that are located in MSAs with transit data. Data is aggregated to the year level and spans 12 years, 2008-2019. Transit exit is generalized to the zip code level, as that is the most granular information provided in the Nielsen panel. Zip code level controls are from the American Community Survey and include median income, population, and racial makeup.

3 Transit Exit

3.1 Effects of Public Transit Exit on Consumer Shopping Habits

I use an event study framework to measure the effects of public transportation exit in a neighborhood on the shopping habits and nutritional intake of households in zip codes without grocery stores. The sample contains 5,127 zip codes in 138 metro areas, over the period 2008-2019. Because bus stop exit is not random, the design exploits changes in the timing of stop exit instead of the exit itself. The control group for all specifications is households that have lost transit in other periods. A balance test for the treatment and control group is presented in A.3 in the appendix, and shows that the treated group is not significantly different from the control group. In the primary specification y is the quantity of trips to a grocery store. Stores that fall into the grocery category include traditional grocery stores and superstores. Since stops were removed at different times, it is possible that difference-in-difference and event study estimates are biased by comparisons between early and late treated units. Because of this, I employ an empirical method modeled off of Callaway and Sant'Anna (2021), which runs pairwise difference in difference to better isolate the impact of timing of the stop opening or closing, which eliminates negative weighting concerns. Each cohort of households that lose a transit stop, meaning they lose the stop in the same year, t, is represented by g. The group-time ATT is:

$$ATT(g,t) = E[Y_t^1 - Y_t^0 | G_g = 1]$$

Where G_g is a dummy variable that equals one if the household is in cohort g. Each group's ATT is:

$$ATT_{(g,t)} = E[(\frac{G_g}{E[G_g]} - \frac{\frac{\hat{p}(X)C}{1-\hat{p}(X)}}{E[\frac{\hat{p}(X)C}{1-\hat{p}(X)}]})(Y_t - Y_{g-1})]$$

G_g is a dummy variable that equals one if the household is in cohort g. C is a dummy variable that equals one if it is in the comparison group, which is households that have not yet lost their transit stop. $\hat{(p)}$ is the propensity score. These cohort ATTs are combined to create event study parameters.

$$\delta^{es} = \sum_{g=2}^{\tau} \sum_{t=2}^{\tau} 1\{t - g + 1 = e\} P(G_g = 1 | \text{Treated for} \geq e \text{ periods}) ATT(g,t)$$

δ_{es} provides the average treatment effect for units that have been treated for e periods.

A traditional event study method is used for robustness. Formally, the specification is as follows:

$$y_{i,t} = \sum_{j=-3}^{3} \beta_j D_{st+j} + \eta_z + \gamma_t + \epsilon_{ist}$$

where j is how many years before or after a household loses a stop. η_z is a vector of zip code fixed effects γ_t is the year fixed effect. D_{st+j} is the product of indicators for the state (treated or not treated) and time (before/after treatment).

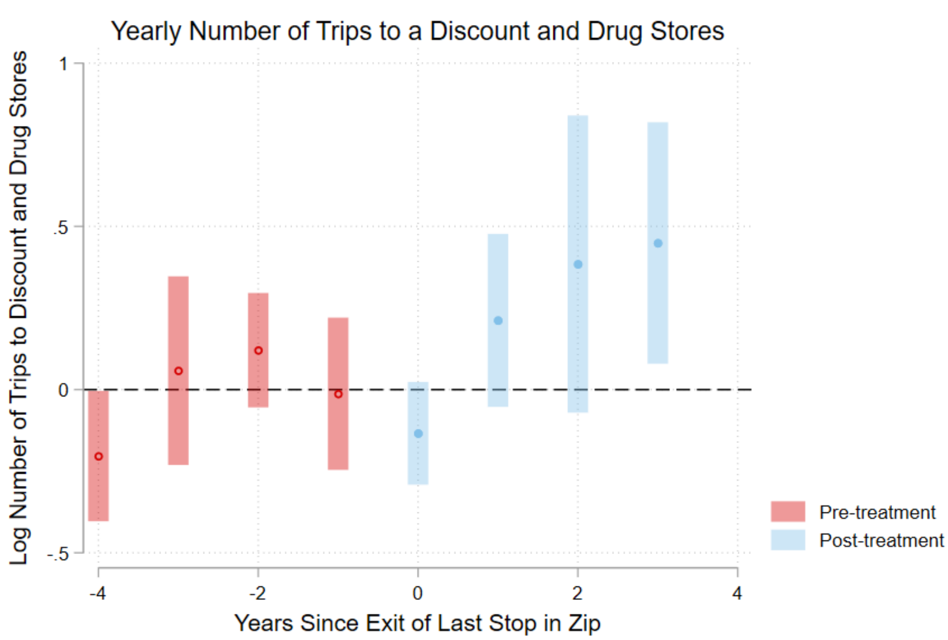
Figure 2: Event Study: Impact of Stop Exit on Number of Trips to Grocery

Event study using the Callaway Sant'Anna method on log of the number of all trips made in a year by a household in that zip code. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. Includes zip code and year fixed effects.

Figure 2 explores the effect of public transportation exit in a zip code on the number of trips that households in that neighborhood make to a grocery store. The Callaway Sant'Anna method is used, with households that have not yet experienced a loss of their public transportation options as the comparison group, as well as year and zip code fixed effects. Figure 2 documents a negative and highly significant impact of the exit of public transportation on number of yearly trips made to a grocery store. This result is persistent over three years following the exit of transportation options. The exit of all public transportation options in a food desert neighborhood creates a roughly 9% decrease in the number of trips made to a grocery store for three years following the exit of transit options.

Figure 3 explores the impact of transit exit on shopping trips to other types of stores, specifically drug and dollar stores. The same specification is used as in figure 2, with households that have not yet lost their transit stops as the comparison group. This figure documents a persistent, positive impact of the exit of public transportation options on the number of yearly trips made to discount and dollar stores. Figures 2 and 3 together demonstrate a movement toward discount and dollar store shopping and away from grocery store shopping in the three years following the exit of public transportation options in a neighborhood.

Figure 3: Event Study: Impact of Stop Exit on Number of Trips to Drug and Dollar Stores



Event study using the Callaway Sant'Anna method on log of the number of all trips made in a year by a household in that zip code. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. Includes zip code and year fixed effects.

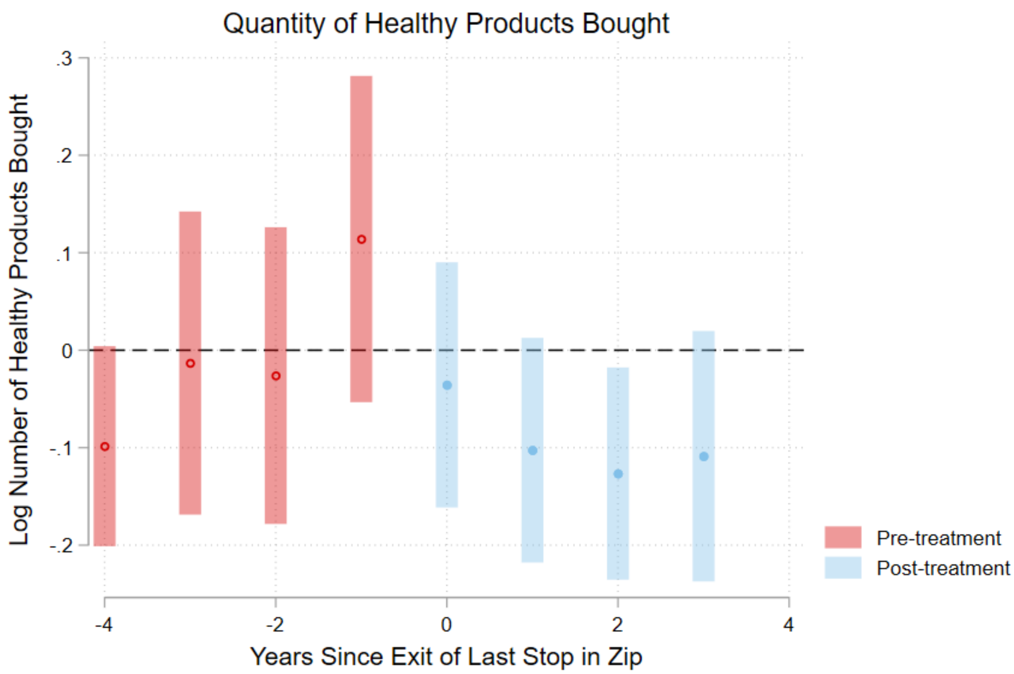
I run several robustness checks. Figure A.2 in the appendix shows the impact of transit exit on grocery store trips using the traditional event study model, which yields results in line with figure 2. Figure A.3 shows a similarly negative, persistent impact when using the percent of grocery trips per year as a fraction of all trips as the dependent variable, rather than number of trips, as in the previous specifications. Figure A.5 in the appendix uses the event study model to show the impact of transit exit on trips to discount and drug stores. Figure A.5 in the appendix breaks the impact on non-grocery out into groups. In particular, food deliveries make up a very small percentage of the overall trips in the Nielsen data, as seen in table A.2.

3.2 Effects of Public Transit Exit on Nutrition

As households change where they shop, they also change what they are buying. I use the same Callaway Sant'Anna framework to study whether the exit of public transportation options in a zip code changes the overall nutritional makeup of the goods households buy. I use the quantity of healthful foods and the quantity of unhealthful foods as the new dependent variable.

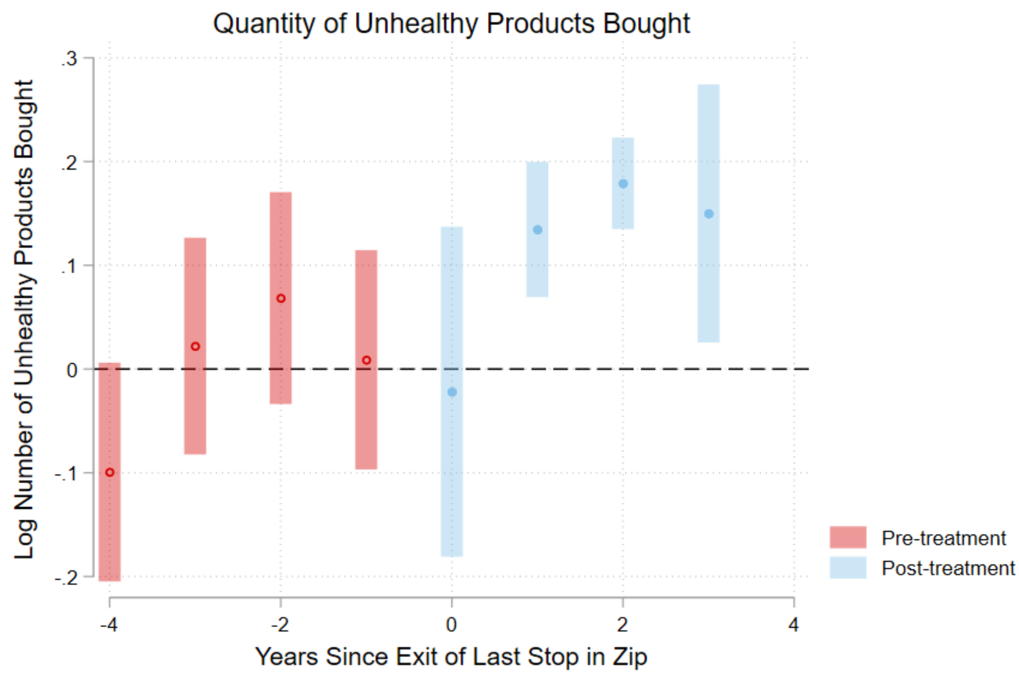
Figure 4 explores the impact of transit exit on the amount of healthy foods households purchase. Households purchase fewer healthy foods for the three years following the exit of public transportation options in their zip codes. Figure 5 shows a mirrored result for unhealthy foods. Households in zip codes that lose public transportation options in their zip code purchase more unhealthy foods for three years following. This result is statistically significant.

Figure 4: Event Study: Impact on Nutrition: Healthy Foods



Event study using the Callaway Sant'Anna method on the impact of stop exit in a zip code on the quantity purchased of healthy foods. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. Includes zip code and year fixed effects.

Figure 5: Event Study: Impact on Nutrition: Unhealthy Foods

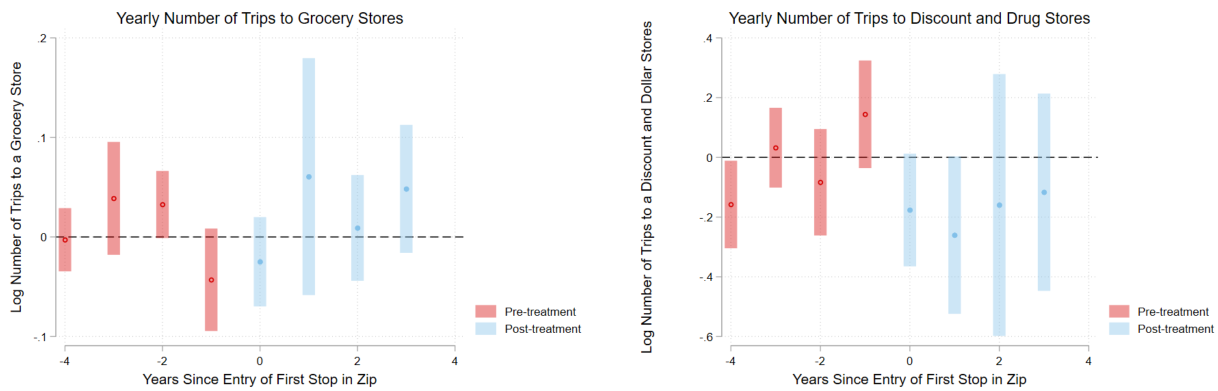


Event study using the Callaway Sant'Anna method on the impact of stop exit in a zip code on the quantity purchased of unhealthy foods. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. Includes zip code and year fixed effects.

4 Effects of Public Transit Entry on Consumer Shopping Habits and Nutrition

Households that experience transit entry in their zip code do not see symmetric changes to their shopping habits. This is consistent with the literature, including Oster (2018) which uses the Nielsen Homescan data to find that individuals do not change their consumption habits following a diabetes diagnosis. Households have established patterns of behavior, and do not change their consumption habits in response to new information. Likewise, I find that households in food deserts do not change their shopping habits in response to the addition of public transportation options in their zip code. Figures 6 demonstrates that households do not increase the number of trips they take to a grocery store following the entry of transit in their zip code. Similarly, they do not change the number of trips that they take to discount and drug stores.

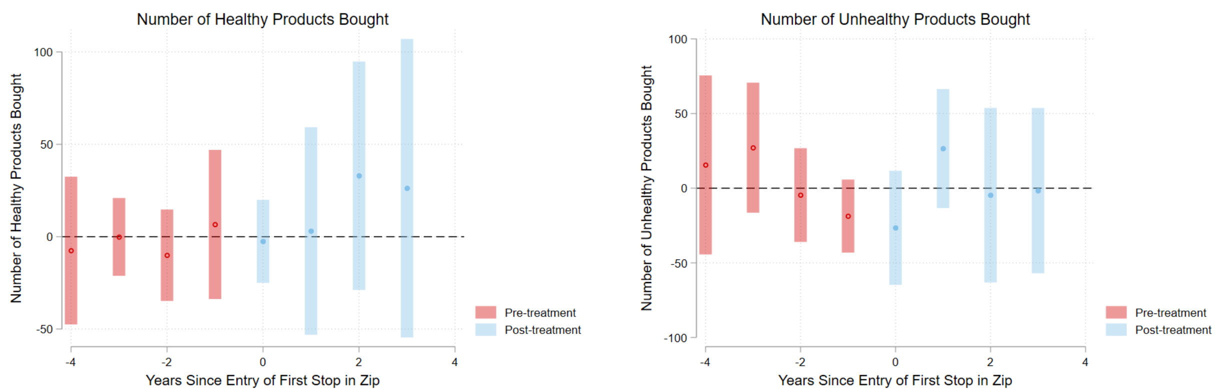
Figure 6: Event Study: Impact of Stop Entry on Number of Trips to Grocery, Discount and Drug Stores



Event study using the Callaway Sant'Anna method on the impact of stop entry in a zip code on the number of trips to grocery stores in the left panel and drug and discount stores in the right panel. Control group is zip codes that eventually gain a stop, among zip codes with no grocery store. Includes zip code and year fixed effects.

There is no change in the healthfulness of consumers' yearly purchases following the entry of public transportation options. Figure 7 shows that both the quantity of healthful products and the quantity of unhealthful products remains unchanged.

Figure 7: Event Study: Impact of Stop Entry on Quantity Purchased of Healthy, Unhealthy Foods



Event study using the Callaway Sant'Anna method on the impact of stop entry in a zip code on quantity of healthy foods purchased in the left panel, and the quantity of unhealthy foods purchased in the right panel. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. Includes zip code and year fixed effects.

5 Conclusion

This research adds an important and currently unstudied dimension to our understanding of food insecurity and poverty in American cities; there is currently no convincing work documenting the causal relationship between transit access and nutrition. I also contribute an original data set of all transportation infrastructure changes across 138 cities in the U.S. over 12 years.

This project holds economic and policy implications for alleviating food deserts and nutritional inequality. Public transportation is an important resource for poor, urban households in food deserts. While entry of transit options in a neighborhood does not directly impact grocery shopping frequency, the removal of transit options in a food desert decreases the percentage of trips to a grocery store by 7%. This is paired with an increase in the number of yearly trips made to discount and drug stores. As a result, households buy fewer healthy products and more unhealthy products in the years following transit exit in their neighborhood.

These findings are particularly relevant today, as pandemic era budget concerns and decreased ridership have triggered a rise in cuts to public transportation networks. In Atlanta, 70 of the city's 110 bus routes have been suspended. Indianapolis removed 500 stops in 2020. 19 of Washington's 91 stations are set to close (NYTimes (2020)). Cuts to transit networks directly impact urban households in food deserts' access to nutritious food.

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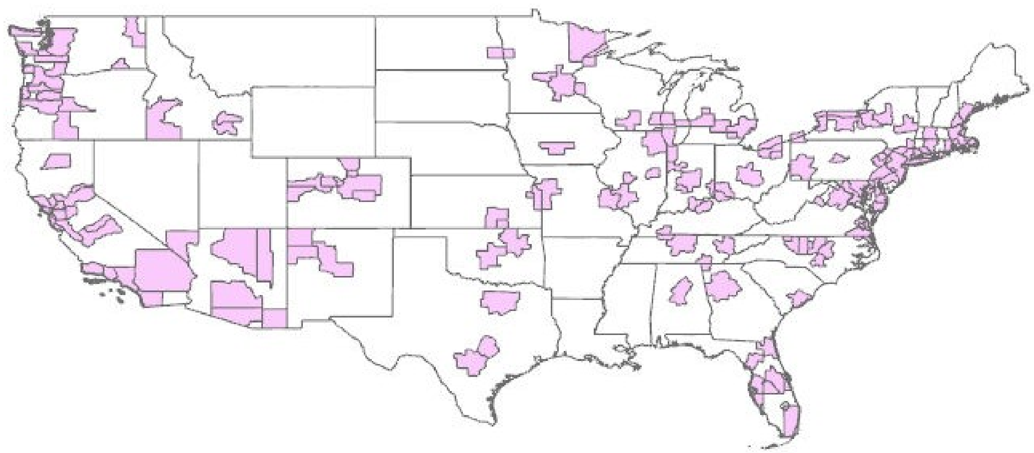
A Appendix Tables and Figures

Figure A.1: Map of Cities in Transit Data



Map gives the location of the 138 total cities are included in the data.

Table A.1: Nielsen Food Groups and Their Healthfulness Status

Product Group	Fraction Healthful	Fraction Not Healthful
SEAFOOD - CANNED	1	0
FRESH PRODUCE	1	0
COFFEE	1	0
EGGS	1	0
NUTS	1	0
FRUIT - DRIED	1	0
FRESH MEAT	1	0
VEGETABLES - CANNED	0.96	0.04
JUICES, DRINKS-FROZEN	0.88	0.13
TEA	0.88	0.13
FRUIT - CANNED	0.83	0.17
BABY FOOD	0.8	0.2
VEGETABLES-FROZEN	0.8	0.2
JUICE, DRINKS - CANNED, BOTTLED	0.78	0.222
UNPREP MEAT/POULTRY/SEAFOOD-FRZN	0.72	0.28
SHORTENING, OIL	0.6	0.4
CEREAL	0.6	0.4
SALAD DRESSINGS, MAYO, TOPPINGS	0.6	0.4
SPICES, SEASONING, EXTRACTS	0.58	0.42
CONDIMENTS, GRAVIES, AND SAUCES	0.5	0.5
VEGETABLES AND GRAINS - DRIED	0.5	0.5
PACKAGED MILK AND MODIFIERS	0.5	0.5
CHEESE	0.5	0.5
YOGURT	0.5	0.5
PICKLES, OLIVES, AND RELISH	0.33	0.67
PREPARED FOOD-DRY MIXES	0.29	0.71
MILK	0.29	0.71
DESSERTS/FRUITS/TOPPINGS-FROZEN	0.25	0.75
ICE CREAM, NOVELTIES	0.25	0.75
SNACKS, SPREADS, DIPS-DAIRY	0.25	0.75
BREAKFAST FOOD	0.25	0.75
JAMS, JELLIES, SPREADS	0.22	0.78
SNACKS	0.177	0.83
PREPARED FOOD-READY-TO-SERVE	0.14	0.86

Nielsen Food Groups and Their Healthfulness Status (cont)

Product Group	Fraction Healthful	Fraction Not Healthful
COT CHEESE, SOUR CREAM, TOPPINGS	0.14	0.86
PREPARED FOODS-FROZEN	0.14	0.86
SOFT DRINKS-NON-CARBONATED	0.11	0.89
DRESSINGS/SALADS/PREP FOODS-DELI	0.06	0.94
BAKING SUPPLIES	0.04	0.96
CANDY	0	1
CARBONATED BEVERAGES	0	1
BAKING MIXES	0	1
BREAD AND BAKED GOODS	0	1
PASTA	0	1
COOKIES	0	1
BEER	0	1
SOUP	0	1
BAKED GOODS-FROZEN	0	1
LIQUOR	0	1
SUGAR, SWEETENERS	0	1
PUDDING, DESSERTS-DAIRY	0	1
FLOUR	0	1
TABLE SYRUPS, MOLASSES	0	1
GUM	0	1
BREAKFAST FOODS-FROZEN	0	1
BUTTER AND MARGARINE	0	1
DESSERTS, GELATINS, SYRUP	0	1
DOUGH PRODUCTS	0	1
PACKAGED MEATS-DELI	0	1
PIZZA/SNACKS/HORS DOEURVES-FRZN	0	1
WINE	0	1
CRACKERS	0	1

Breakdown of the product groups in the Nielsen panel, and what fraction of products in each category are reccomended for increased consumption (healthful) vs limited consumtion (unhealthful) by the DGA.

Table A.2: Household Shopping Patterns

	(1) Has Grocery		(2) No Grocery		(3) Difference	
	mean	sd	mean	sd	b	t
Panel A: Shopping Patterns						
Grocery Store	0.47	0.21	0.45	0.22	-0.02***	(-27.87)
Discount Store	0.21	0.17	0.25	0.19	0.04***	(48.86)
Drug Store	0.07	0.09	0.06	0.08	-0.01***	(-39.19)
Warehouse Store	0.06	0.10	0.05	0.09	-0.01***	(-26.32)
Convenience Store	0.01	0.05	0.02	0.05	0.00***	(22.68)
Delivery	0.00	0.01	0.00	0.01	-0.00	(-0.53)
Observations	433040		82722			
Panel B: Household Characteristics						
Household Size	2.57	1.38	2.65	1.37	0.08***	(7.21)
Household Income	20.38	5.98	20.22	5.97	-0.17***	(-3.66)
White	0.78	0.42	0.86	0.35	0.08***	(29.57)
Black	0.12	0.32	0.07	0.25	-0.05***	(-23.39)
Hispanic	0.08	0.28	0.06	0.24	-0.02***	(-13.10)
Non-Hispanic	0.92	0.28	0.94	0.24	0.02***	(13.10)
Married	0.61	0.49	0.68	0.47	0.06***	(17.19)
Single	0.18	0.38	0.14	0.34	-0.04***	(-14.32)
Observations	104033		20111		124144	
Panel C: Zip Code Demographics						
AGI	53546.51	45116.07	12001.47	14402.60	-41545.04***	(-71.74)
Population	25920.30	18258.83	6260.39	7602.90	-19659.91***	(-80.67)
White	74.09	21.83	86.65	16.41	12.56***	(35.47)
Black	11.65	17.73	5.57	12.05	-6.08***	(-22.09)
Hispanic	25920.30	18258.83	6260.39	7602.90	-19659.91***	(-80.67)
Observations	7115		4618		11733	

Summary statistics on the grocery shopping habits and demographic characteristics among households in zip codes that have transit stops, by whether or not they have a grocery store in their zip code. Shopping data is from the Neilsen HomeScan 2004-2019, grocery store location data is from the USDA.

Table A.3: Summary Statistics of Treated and Control households

	Treatment		Control		p value
	mean	sd	mean	sd	from t test
Household Size	2.77	1.54	2.57	1.38	0.73
Household Income	20.42	6.17	21.29	5.74	0.06
Perc. With Children	0.29	0.45	0.27	0.44	0.43
Male Head Education	3.14	1.95	3.32	2.00	0.19
Perc. Married	0.74	0.44	0.74	0.44	0.39
Perc. White	0.73	0.45	0.83	0.37	0.58
Perc. Black	0.09	0.29	0.13	0.33	0.99

Table presents summary statistics for treatment and control households. The last column presents p-values from the t-test of the difference in the characteristic between treatment and control ZIP codes. Treatment households are households that experience the removal of a transit stop, while control households are households that experience the removal of transit options at least two years in the future. Households income is binned, with 21 being $50,000-$59,000 per year. Male Head Education is also binned, with 3 being graduated high school and 4 being some college.

Table A.4: Change in Trips to Grocery Store, Discount/Drug Stores

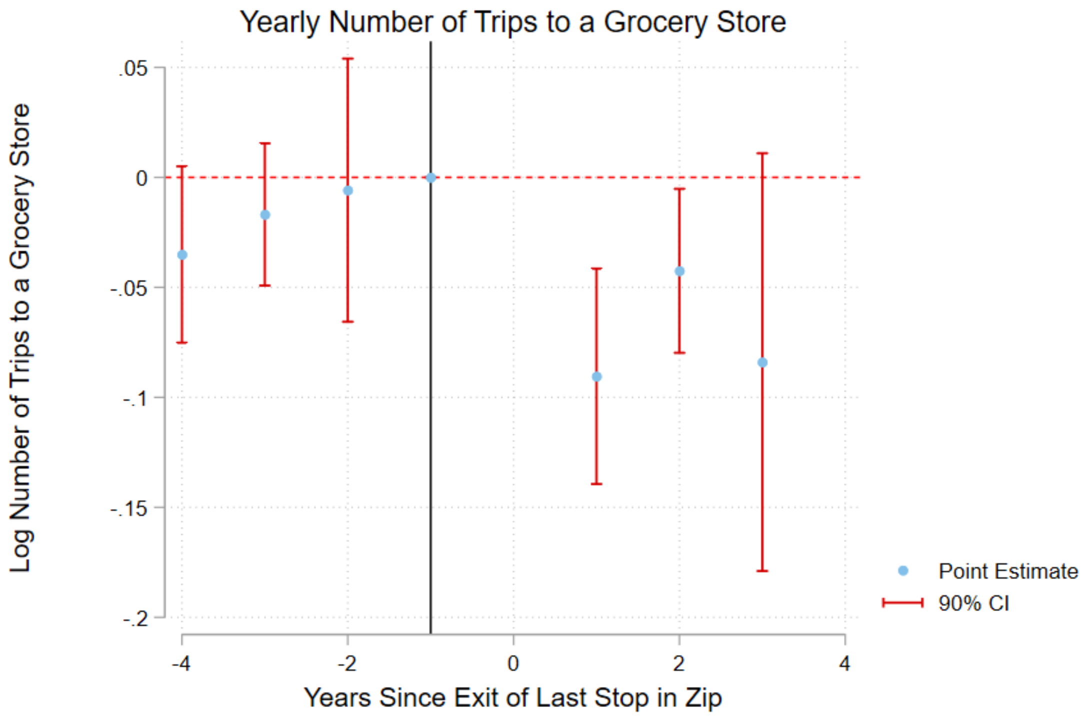
	Grocery	Discount/Drug
Tm4	-0.0551	-0.204**
	(0.0717)	(0.102)
Tm3	-0.0187	0.0580
	(0.0280)	(0.147)
Tm2	0.0147	0.121
	(0.0161)	(0.0894)
Tm1	-0.00399	-0.0128
	(0.0385)	(0.119)
Tp0	0.00971	-0.134*
	(0.0369)	(0.0802)
Tp1	-0.0721***	0.212
	(0.0193)	(0.135)
Tp2	-0.108***	0.385*
	(0.0168)	(0.232)
Tp3	-0.0889***	0.449**
	(0.0243)	(0.189)
Observations		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

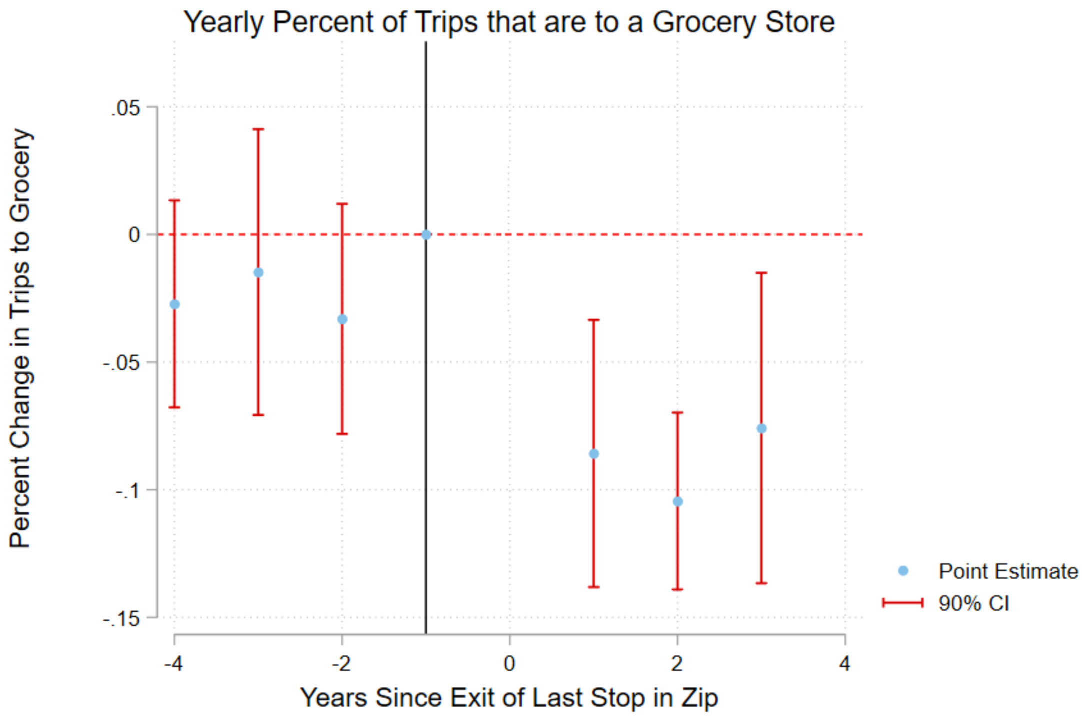
Event study on the impact of transit exit in a zip code on number of trips made to grocery stores and grocery substitutes: discount, dollar and drug stores. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. Includes zip code and year fixed effects.

Figure A.2: Event Study: Impact of Stop Exit on Number of Trips to Grocery



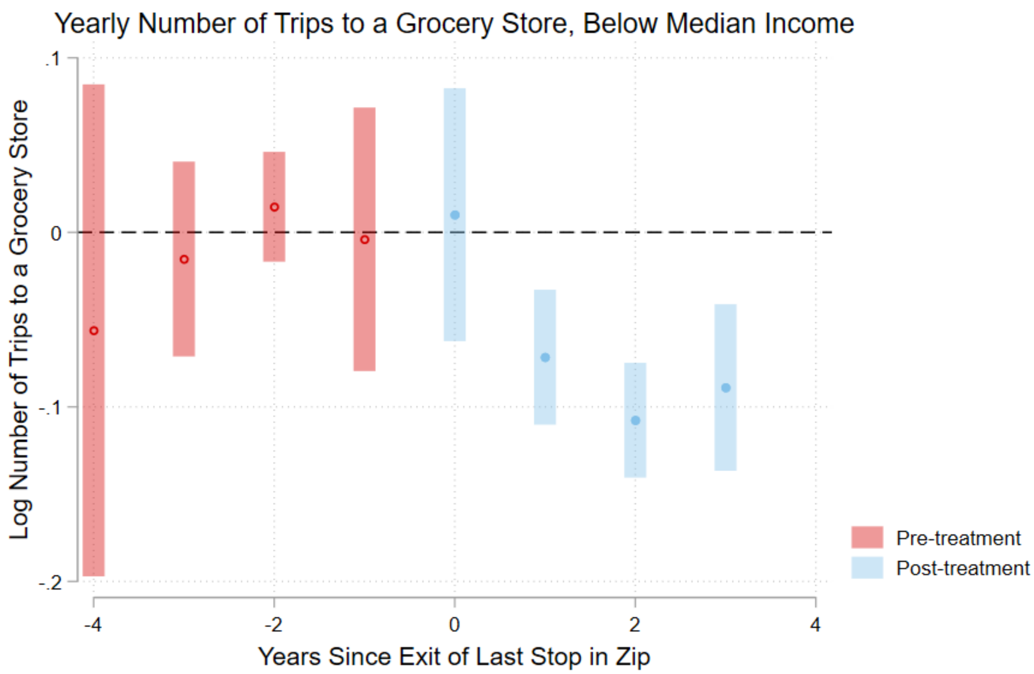
Event study on log of the number of grocery trips made in a year by a household in that zip code. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. The zero year is dropped for noise. Includes zip code and year fixed effects.

Figure A.3: Event Study: Impact of Stop Exit on Percent of Trips to Grocery



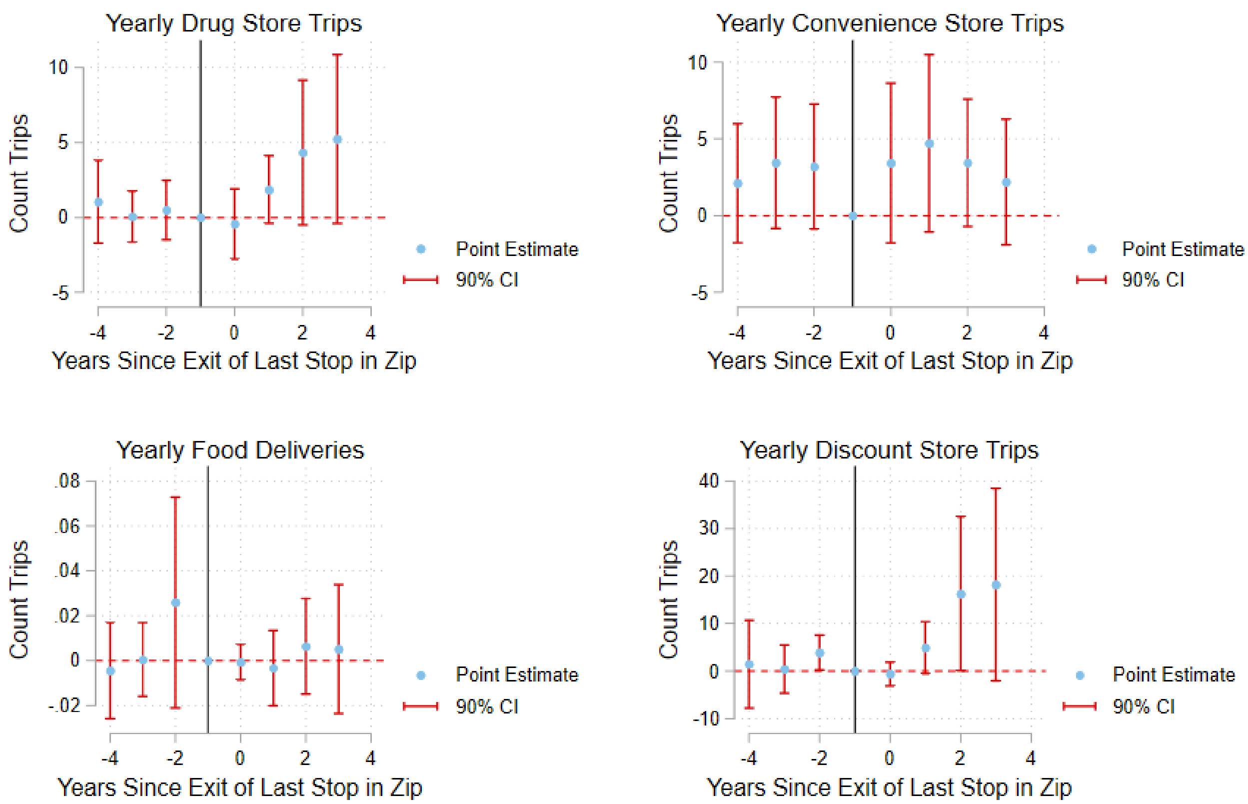
Event study on the impact of transit exit in a zip code on percentage of trips that are to a grocery store as a fraction of all trips made in a year by a household in that zip code. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. The zero year is dropped for noise. Includes MSA and year fixed effects.

Figure A.4



Event study using the Callaway Sant'Anna method on the impact of transit exit in a zip code on number of trips made to grocery stores for families with below median income. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. Includes zip code and year fixed effects.

Figure A.5: Impact of Transit Exit on Trips to Other Types of Stores



Event study on the impact of transit exit in a zip code on number of trips made to other types of stores. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. Includes zip code and year fixed effects.

Figure A.6: Impact of Transit Exit on Trips to Drug, Dollar and Discount Stores Combined

Event study on the impact of transit exit in a zip code on number of trips made to grocery substitutes: discount, dollar and drug stores. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. The zero year is dropped for noise. Includes zip code and year fixed effects.

Table A.5: Change in Number of Healthy Foods, Unhealthy Foods

	Healthy	Unhealthy
Tm4	-0.0985*	-0.0993*
	(0.0524)	(0.0538)
Tm3	-0.0132	0.0221
	(0.0793)	(0.0533)
Tm2	-0.0260	0.0684
	(0.0777)	(0.0521)
Tm1	0.114	0.00888
	(0.0854)	(0.0539)
Tp0	-0.0356	-0.0219
	(0.0641)	(0.0811)
Tp1	-0.103*	0.134***
	(0.0588)	(0.0333)
Tp2	-0.127**	0.179***
	(0.0555)	(0.0225)
Tp3	-0.109*	0.150**
	(0.0655)	(0.0634)
Observations		

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Event study using the Callaway Sant'Anna method on the impact of stop exit in a zip code on the quantity purchased of healthy and unhealthy foods. Control group is zip codes that eventually lose a stop, among zip codes with no grocery store. Includes zip code and year fixed effects. Accumulated endpoint.