Restaurant Advertising Expenditure Trends in US Counties by Race, Ethnicity and Income.

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Abstract. Recent growth in the share of household dollars spent on food consumed outside the home, in combination with growing obesity disparities, has heightened interest in food advertising by geography and population demographics. This study aimed to identify changes in advertising expenditure by US restaurant chains across counties, grouped by income, race and ethnicity. Using expenditure and location data for the top-100 grossing US restaurant chains and county-level demographic information, we measured trends in advertising expenditure at the county level. US counties were split by population density and socio-demographics. Quantile regression analysis was performed to identify baseline differences in total spending within county groups, as well as changes over time. Results show that fast food restaurant chains reported the highest expenditures among the types of restaurants and that the majority of advertising dollars were spent on television advertisements within the highest density counties. Our results show that – for all density types - the lowest levels and the greatest declines of advertising dollars occur among high-income counties and those with a low proportion of Black and Hispanic/Latino residents. In contrast, within the lowest density (rural) counties, the highest expenditure rates occurred in counties with a high proportion of Black and Hispanic/Latino residents, regardless of income. Among the highest density (urban) counties, the highest spending levels were observed in low-income counties. Together, these results suggest that restaurant advertising dollars in high- and low-density counties are consistently targeted towards populations who are also at greater risk for obesity in the United States.

Disclaimers: This article presents analyses conducted by the researchers and is based in part on data from the Nielsen Company (US), LLC and marketing databases provided through Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of

Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the view of Nielsen or its licensors. Nielsen and its licensors are not responsible for, had no role in, and were not involved in analyzing and preparing the results reported herein.

Introduction

For over a decade in the United States, more money has been spent on food consumed away-from-home than on food consumed at-home [1]. Critically, full-service and limited service (e.g. fast food) restaurants, the focus of this analysis, account for 68.8 percent of all food away from home consumption [2]. Given this growth in spending in restaurants combined with the high national obesity rates [3], understanding patterns in restaurant advertising is increasingly important as it influences the American diet and overall food choices [4,5]. For example, experimental evidence documents the effect of food advertising on children's dietary intake, showing that children exposed to more food advertising ate more and were more likely to have obesity [6–8]. There is also research documenting differences in consumer food purchasing by race/ethnicity and socioeconomic status (SES), where communities with low-income and racial minority residents were more likely to consume energy dense, processed, and unhealthy foods. Residents in rural communities were often susceptible to limited access to healthy food options. These differences are further compounded when intersected with both low-income and racial minority residents [9], as well as differences in overall food marketing [10] but much less is known about similar patterns for restaurant advertising. Additionally, restaurant food items, in comparison to food cooked and consumed at home, are often associated with larger portion sizes and a higher caloric and fat intake, which are significant risk factors for obesity [11,12].

Prior research has shown that advertising of unhealthy foods, such as by fast-food restaurants, has been more concentrated in low-income and minority communities [13,14]. This increased exposure to higher caloric foods has been found to be associated with increased weight gain among Black and Latino/a adults [15], and changes in advertising spending have been found to be associated with changes in body mass index (BMI) in low-income counties [16]. In addition to work on overall marketing patterns of food companies [10], a handful of researchers have also documented that exposure to outdoor advertising, specifically billboards, bus benches, bus shelters, storefronts and subways differs by income, race and ethnicity [17–21], and could also vary by the population density, or urbanicity, of the geographic area being marketed. None of these studies, however, focus on differential advertising patterns of restaurants beyond fast-food.

Our work builds on this knowledge and seeks to broaden our understanding of how restaurant advertising expenditure changes over time, across multiple advertising mediums, by geography, race, ethnicity, and income. With the availability of quarterly advertising expenditure across different media and restaurant types and geographic locations of the top-grossing restaurant chains in the United States, our study creates an objective measure of local per capita restaurant advertising in order to examine how changes in restaurant advertising expenditure vary at the county level, accounting for differences defined by county-level income, population density, race and ethnicity.

Methods

- *Data/Measures*

Our study focused on the top 100 grossing US restaurant chains from 2012-2016, identified by annual rankings from the Nation's Restaurant News [22]. Given that the top 100 restaurant chains change from year to year, a total of 107 restaurant chains were included for analysis. Restaurant chains were classified into three categories: fast food (n=49), fast casual (n=17), and full service (n=41). Full service was defined as a restaurant that provides table service. Fast food and fast casual were distinguished based on a list of criteria: (1) no table service available; (2) non-disposable utensils provided; (3) on-site food preparation; and (4) commitment to higher quality, sustainability, and fresh ingredients. Fast casual restaurants met at least 2 of these criteria. Fast food restaurants met less than 2 of these criteria. Supplementary A provides a list of all restaurant chains included and their classifications.

The outcome of interest, per capita restaurant advertising (PCRA), was a derived measure that pulled from three different data sources. (1) Geographic address locations of each restaurant chain were obtained from AggData (www.aggdata.com). (2) Data on quarterly total advertising expenditure by each restaurant chain on all media types (TV, Print, Web, Radio and Other) in each Designated

Market Area (DMA) were obtained from Nielsen. The boundaries of each DMA are presented in Figure 1. Importantly, the boundary of a DMA can span multiple counties. (3) County population data were drawn from the U.S. Census Bureau's 2012-2016 American Community Survey (ACS). Variables include proportion of Black and Hispanic/Latino (BHL) residents by county, median income, proportion of residents with a at least 4-year college degree, unemployment rate, and county square area to calculate county population density. Further details on the three data sources used can be found in Supplementary B.

[FIGURE 1 HERE]

Our outcome, per capita restaurant advertising, described in the equation below, is calculated as a ratio, where the numerator consists of the ratio of the number of restaurants in a given county divided by the number of restaurants in that county's DMA, multiplied by the total DMA expenditure for that restaurant in each year-quarter. The denominator consists of the county population for the observed year. Specifically let i represent a restaurant chain, c represent a county identifier, d a DMA identifier, q the quarter (within year y).

$$PCRA_{cq} = \frac{\sum_i \frac{Restaurant\ location_{icy}}{restaurant\ location_{idy}} \times total\ DMA\ expenditure_{idq}}{county\ population_{cy}}$$

Intuitively, the numerator takes the total expenditures by a particular restaurant chain in a DMA and spreads it out across the counties in that DMA in proportion to the number of restaurants that chain has in each county. These weighted restaurant expenditures were then summed over the 107 restaurants in the sample. Importantly, a county PCRA measure only includes advertising expenditures for a particular restaurant chain if that chain has a location in that county. This calculation produces a county-level measure of total restaurant advertising expenditure which is then scaled by the county population.

- ***Statistical Analysis***

Descriptive statistics were calculated to examine the distribution of per capita restaurant advertising (in dollars) by restaurant chain and media type, as well as county characteristics. Counties were then classified by population density (population per square mile) and divided into quartiles. The first quartile consisted of counties with the lowest density (rural). The second quartile contained low-density (suburban-1) counties. The third quartile contained moderate density (suburban-2) counties. The fourth quartile contained the highest density (urban) counties. All 3,141 US counties were included for analysis.

Counties were then further classified demographically, to highlight the cross-section of two key demographic features, income and race/ethnicity [9]. Four categories were defined based on ACS-obtained information of racial and ethnic resident composition and median income level at baseline (2012) to construct relatively evenly distributed categories. County groups were first stratified based on which counties had proportions of Black and Hispanic/Latino (BHL) residents above or below the overall median (10%), labeled as *High-BHL* and *Low-BHL* respectively. County groups were further stratified based on which counties had a median income above or below the 2012 US median ($47,220), labeled as *High-Income* and *Low-Income,* respectively.

To identify changes in per capita restaurant advertising expenditure over time, a linear quantile mixed model was run, with PCRA expenditure treated as the primary outcome and county type (Income/BHL) as the primary exposure. Implementation of a quantile mixed model allowed us to account for outlying restaurant chains that observed considerably higher or lower PCRA expenditure dollars. County-level covariates were included in the model to adjust for the county-level proportion of residents with at least a bachelor's degree, and the county-level unemployment rate. Additional fixed effects were included to adjust for time (indexed as quarterly-year) and election year was added to account for potential changes in advertising trends driven by political cycles (2012, 2014, 2016). An interaction term of Income-BHL county type and time was also included to account for temporal variation by county type. Due to the repeated measures observed for each county, within county variation was adjusted for via a random intercept indexed at the county level. To account for differences in trends by population density, regression analysis was stratified according to the four population density quartiles, resulting in four sets of estimates. A subsequent stratified analysis was performed to examine if expenditure differences and changes over time were observed by restaurant type (fast food, fast casual, full service).

All data wrangling and cleaning were processed in STATA, R and Python software. Statistical analysis and visualizations were performed in R using the following packages: dplyr [23], nlme [24], lqmm [25], ggmap [26] and ggplot2 [27].

Results

Table 1 describes the median per capita restaurant advertising expenditure for the 107 restaurant-chains. Overall, PCRA had a slight decline from 2012-2015, from \$3.59 to \$3.43, but reversed trend in 2016 (\$3.56). For an average sized county in the United States, with approximately 100,000 residents, this is equivalent to \$350,000. For more populous urban counties, with at least 1 million residents, this is equivalent to at least \$3.5 million dollars. By restaurant type, fast-food restaurants had the highest PCRA expenditure with an average of \$2.81 over the five-year timespan, while fast-casual restaurants had the lowest. TV advertising had the highest median PCRA expenditure across media types. Radio advertising had the lowest median PCRA expenditure.

[TABLE 1 HERE]

Table 2 describes baseline county characteristics across the four population density quartiles. In 2012, the counties with the highest density were also the counties with the highest median income and the highest proportion of residents with four years of college or more. The mean proportion of Black and Hispanic/Latino residents ranges from a low of 15.4% in the moderate density (suburban-2) counties to a high of 21.9% in the highest density (urban) counties. This indicates a positive skew in our distribution of Black and Hispanic/Latino residents, such that there are counties with much higher proportions of this residential demographic pulling the means above the overall median of about 10%.

Within the population density groupings, we observed significant variation in the income/BHL makeup of the counties. Over half of the High-Income/High-BHL counties were in the highest density (urban) counties. By contrast, Low-Income/High-BHL counties were more evenly distributed across all density groups.

[TABLE 2 HERE]

The results of our primary analysis are presented in Figure 2 and Table 3. Figure 2 provides a visualization of how the median per capita restaurant advertising changed over time by county (Income/BHL) type across the four population density quartile groups, unadjusted for confounders. Results for each density group are displayed in separate panels. Table 3 provides the parameter estimates from the linear quantile mixed model, which are adjusted for confounders. Results from these two analyses confirm the same set of findings.

[FIGURE 2 HERE]
[TABLE 3 HERE]

Amongst the lowest population density (rural) counties, High-BHL counties, regardless of income, had higher restaurant advertising expenditures than Low-BHL counties. Over time, the expenditures in High-BHL counties appeared stably high, while those in Low-BHL counties appeared to decrease slightly (Figure 2, panel a). These trends are supported statistically, after adjusting for key confounders (Table 3, column 1). Compared to the reference group, Low-BHL county subgroups indicated an increase of $1.50, but changes over time were not statistically significant.

For low population density (suburban-1) counties, differences were still large between High-Income counties along lines of BHL, but there were no longer differences between Low-Income counties along lines of BHL. High-Income/High-BHL counties exhibited the highest levels of advertising expenditures, and High-Income/Low-BHL counties exhibited the lowest levels of expenditures (Figure 2, panel b). After adjusting for confounders, High-Income/High-BHL counties had about $1.46 more median advertising expenditures than High-Income/Low-BHL counties (Table 3, column 2). Unlike the rural counties, there was no statistically significant differentiation in expenditures among low-income counties by high- or low-BHL status. Trend wise, spending in these low-density suburban counties decreased slightly but significantly, except for Low-Income/High-BHL counties where advertising expenditures were flat.

For moderate population density (suburban-2) counties, no statistically significant differences in the median levels of expenditures by income or Black and Hispanic/Latino status were observed. Over time there was a slight increase in expenditures in low-income counties relative to high-income counties, regardless of Black and Hispanic/Latino status. For example, the coefficients on the low-income county indicators interacted with time indicated an increase of one to three cents per quarter in low-income counties relative to the reference group of High-Income/Low-BHL counties which saw a decrease in spending of about one cent per quarter over the sample time frame (Table 3, column 3).

For the highest population density (urban) counties, differences amongst high- and low- income counties were more pronounced, where lower income counties experienced higher advertising spending compared to higher income counties regardless of Black and Hispanic/Latino status (Figure 2, panel d). After adjusting for confounders, advertisers spent about $1.32 more per capita in Low-Income/Low-BHL urban counties than in High-Income/Low-BHL urban counties and about $1.12 more in Low-Income/High-BHL urban counties (Table 3, column 4). Differences between high- and low- BHL counties with high incomes were not statistically significant. Adjusted trends in urban counties showed high-BHL counties, rather than the low-income counties had statistically significant differences. While advertising expenditures in High-Income/Low-BHL counties decreased by about two cents per quarter, expenditures in high-BHL counties showed a minimal decrease in comparison (Table 3, column 4). Thus, among urban counties, the differences in levels of spending were largest by income status while the differences in trends of spending over time were largest by Black and Hispanic/Latino status.

Table 4 provides the regression output for each restaurant type across the different population density groups. Overall, results at the fast-food level were consistent with those seen in the pooled analysis. In rural counties, significance was only found amongst fast food restaurants, consistent with results in Table 3. Statistical significance was not evident for fast casual and full-service restaurants.

Some differences emerged from the overall analysis in low population density (suburban-1) counties. Fast-food restaurant levels of advertising spending were significantly different across all three comparative income/BHL groups, whereas in pooled results differences only emerged between High-Income/High-BHL and High-Income/Low-BHL. Temporal effects within Low-Income/High-BHL counties for fast food restaurants were consistent with overall results. In contrast, in suburban-1 counties fast casual restaurants increased spending relatively more in High-

Income/High-BHL counties and Low-Income/High-BHL counties, relative to High-Income/Low-BHL counties, but magnitudes here were small. No significant differences were found amongst full-service restaurants.

Moderate population density (suburban-2) counties had consistent results with the overall analysis amongst fast-food restaurants, with additional significance noted in the temporal effect of High-Income/High-BHL counties. Changes in spending within fast casual restaurants were only significantly different from the baseline group within Low-Income/High-BHL counties. Levels of spending within full-service restaurants were only significantly different from the baseline group within High-Income/High-BHL counties, consistent with the overall analysis, with no significant differences in changes over time.

The highest population density (urban) counties had the most different results from the overall analysis. Differences in levels of spending among fast casual and full-service restaurants were mostly consistent with overall results, but we no longer observed differences in levels of spending across county types within fast food restaurants. In terms of changes over time, we found similar results across all restaurant types, with the largest differences emerging within fast food restaurants.

Discussion

This study identified county-level changes in advertising expenditure by US restaurant chains by income, race and ethnicity. Fast food restaurant chains reported the highest expenditure, and the majority of advertising dollars were spent on television advertisements. In stratified analyses by population density, expenditure patterns varied by income and the concentration of Black or Hispanic/Latino residents. Specifically, rural counties had higher restaurant expenditure rates in counties with a high level of Black and Hispanic/Latino residents. Urban counties had higher restaurant expenditure rates in low-income counties. The intersection of race/ethnicity and income status was most apparent in suburban counties where higher restaurant expenditure was observed among counties with low income and high level of Black and Hispanic/Latino residents whereas lower restaurant expenditures were observed among counties with high income and a low level of Black and Hispanic/Latino residents. Taken together, these results suggest that restaurant advertising dollars in high density counties are consistently targeted towards county populations that are at greater risk for obesity in the United States.

Within fast casual restaurants, the largest difference in restaurant expenditure was observed in urban counties characterized by high income with a high level of Black and Hispanic/Latino residents compared to those characterized by high income with a low level of Black and Hispanic/Latino residents. Within full-service restaurants, the largest differences in restaurant expenditure was observed by county income. Further research is needed to understand what factors are driving these differences for fast-casual and full-service restaurants within certain types of counties.

Few studies have examined differences in food advertising by medium type (e.g. TV or print) and by county characteristics [10]. To our knowledge, no study to date has focused specifically on advertising expenditure across the restaurant landscape of the highest grossing chains (regardless of restaurant type) including all possible media types, as well as by restaurant type. Further, while the majority of studies relied on a cross-sectional design, our data allowed us to capture longitudinal trends for the entire country. This was achieved by the development of our objective measure for local per capita restaurant advertising, derived from multiple national data sources and adapted from Bleich et al. [15]. Our results were consistent with prior research but provide greater context with the additional understanding of expenditure by restaurant types.

Despite these novel findings, our study contained some limitations. One main limitation is data availability. Working across multiple national databases constrained our study to data that were available across all sources and could be effectively harmonized. This constrained our study time frame to 2012-2016. Still, the results offer a comprehensive picture of a complex relationship between restaurant expenditures, geography and population characteristics that is not currently available in the published literature. Additionally, a total of 81 restaurant chains included in this analysis are still amongst the top 100 restaurant grossing chains today [28]. Another limitation is that our analysis relied on advertising expenditures, which does not necessarily translate to exposure, or how much people directly interact with advertisements. Different media types vary in cost, and these may not directly correlate with exposure. For example, web/online advertising is lower in cost but has a larger potential of audience reach compared to TV advertising which has the highest expenditure of all media types [29].

This is the most rigorous study to date looking at trends in advertising expenditures among the top 100 grossing restaurants by geography and population demographics. Our results suggest that restaurant advertising dollars in high- and low-density counties are consistently targeted towards populations who are also at greater risk for obesity in the United States. This knowledge offers important insights into widening obesity disparities and helps identify concrete opportunities for policy intervention. It also underscores important future research such as evaluating the impact of chain restaurant advertising on major chronic disease risk factors, such as obesity, across US counties.

Data Availability Statement

Location data of restaurant chains are available through AggData (www.aggdata.com) for purchase. Advertising expenditure data was obtained from Nielsen Ad Intel via a partnership with University of Chicago Booth School of Business. This data is not publicly available but may be made available through a subscription contract with Kilts Data Center for Marketing.

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Figure 1. Map of 209 Designated Marketing Areal units (DMAs), which are geographically defined by Nielsen Ad Intel and separated by different colors. County boundaries are overlayed and distinguished with black border lines.

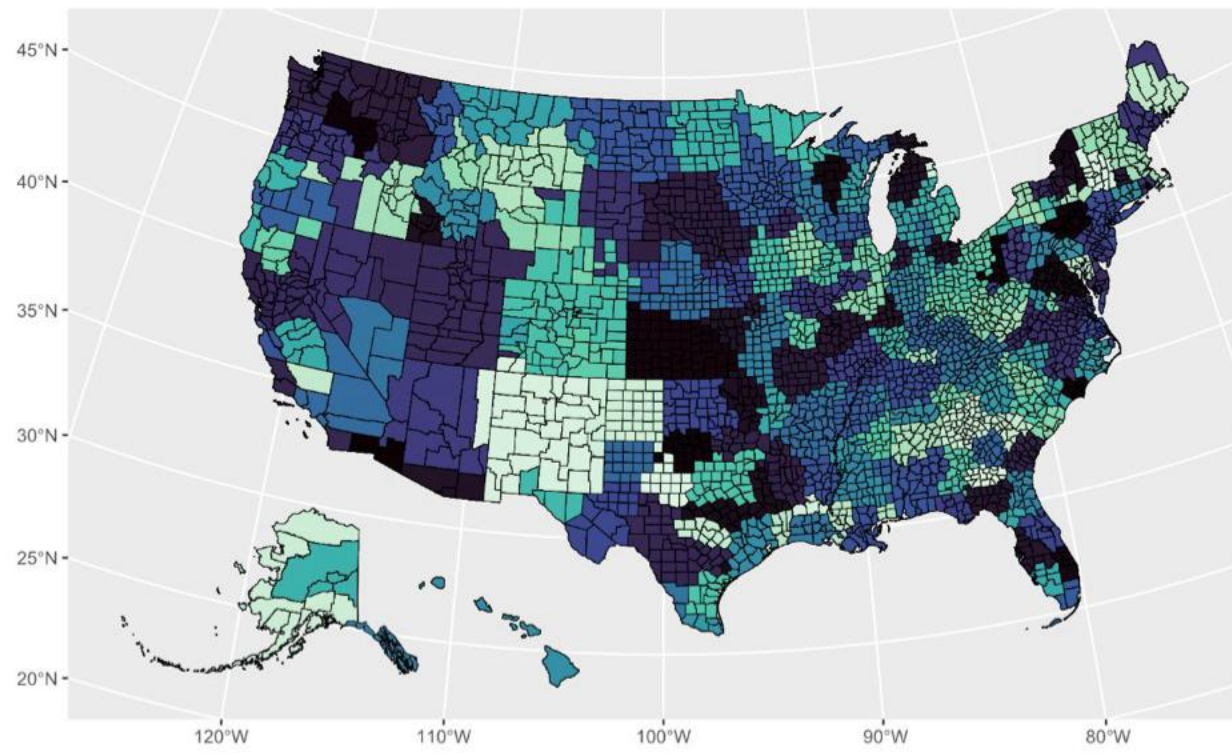
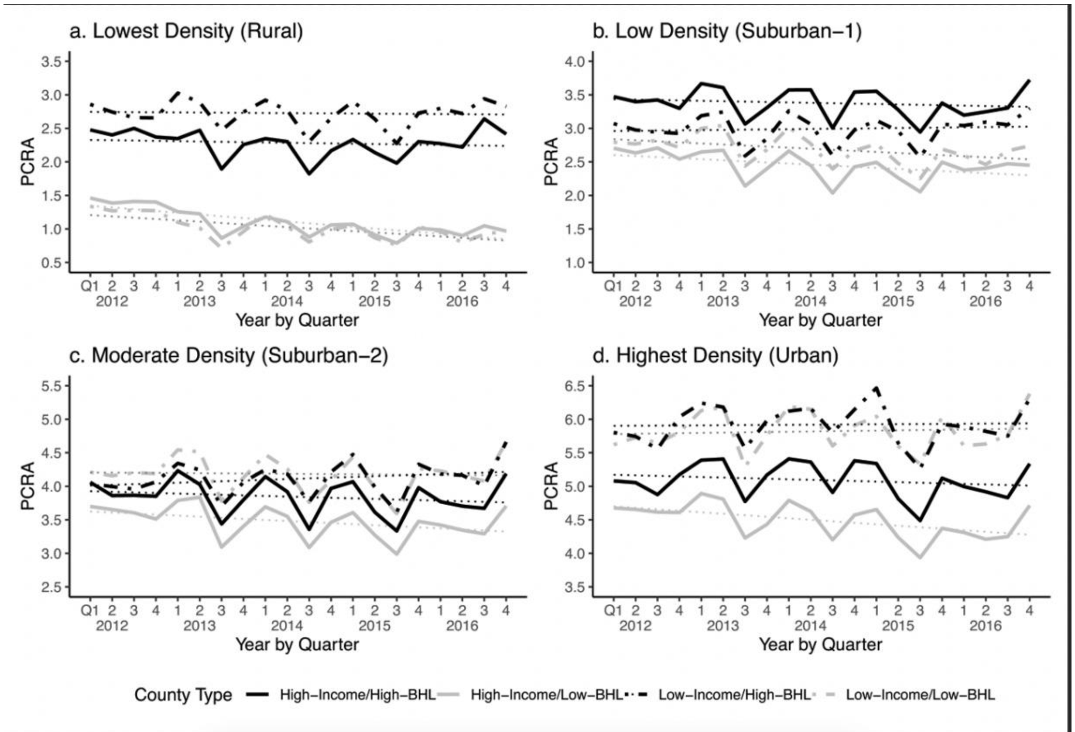


Figure 2. Trends over time of median per capita restaurant advertising in dollars, stratified by county population density.



Note: Solid lines denote counties with median income above the national average. Dashed lines denote counties with median income below the national average.

Table 1 Median per capita restaurant advertising expenditures by restaurant and media type, in dollars

	2012	2013	2014	2015	2016
Overall	$3.59	$3.56	$3.55	$3.43	$3.56
Restaurant Type					
Fast Food	$2.80	$2.78	$2.85	$2.78	$2.85
Fast Casual	$0.00	$0.00	$0.00	$0.00	$0.00
Full Service	$0.55	$0.52	$0.45	$0.39	$0.47
Media Type					
TV	$3.32	$3.28	$3.30	$3.17	$3.32
Print	$0.04	$0.05	$0.04	$0.02	$0.01
Web	$0.02	$0.02	$0.02	$0.03	$0.04
Radio	$0.06	$0.03	$0.02	$0.01	$0.00
Other	$0.05	$0.05	$0.05	$0.06	$0.05

Notes: Sample includes 3,141 US counties.

Table 2 Baseline county characteristics stratified by population density

	Overall	Lowest Density (Rural)	Low Density (Suburban-1)	Moderate Density (Suburban-2)	Highest Density (Urban)
Mean Estimate					
Population Density, ppl/mi2	364.1	6.7	29.3	71.1	1,348.3
Median Income, in $000's	$47.22	$45.77	$42.38	$45.02	$55.69
Black or Hispanic/Latino, %	17.9%	16.2%	18.3%	15.4%	21.9%
Unemployment, %	6.4%	5.6%	7.0%	6.8%	6.2%
4 Years College or More, %	20.7%	19.1%	16.5%	18.4%	29.0%
County Sample Type (Count, N)					
Low-Income/High-BHL	815	189	266	216	144
Low-Income/Low-BHL	757	227	241	224	65
High-Income/High-BHL	717	102	88	125	402
High-Income/Low-BHL	852	267	190	220	175
N	3,141	785	785	785	786

Notes: Mean estimates reflect county characteristics in 2012 by neighborhood density. Sample count represents the number of counties in our sample that are identified in each density group.

Table 3 Quantile regression estimates reflecting the association between county income/BHL category and restaurant advertising expenditures

	Lowest Density (Rural)	Low Density (Suburban-1)	Moderate Density (Suburban-2)	Highest Density (Urban)
Low-Income/High-BHL	1.50 (0.35)***	0.66 (0.36)	-0.07 (0.43)	1.12 (0.29)***
Low-Income/Low-BHL	-1.84 (0.21)	0.48 (0.23)	0.44 (0.43)	1.32 (0.53)*
High-Income/High-BHL	1.50 (0.41)**	1.46 (0.46)*	0.50 (0.37)	0.43 (0.33)
Time	0.00 (0.00)	-0.02 (0.01)**	-0.01 (0.01)*	-0.03 (0.01)**
Low-Income/High-BHL*Time	0.00 (0.00)	0.01 (0.01)**	0.03 (0.00)***	0.02 (0.01)**
Low-Income/Low-BHL*Time	0.00 (0.00)	0.00 (0.00)	0.01 (0.00)***	0.01 (0.01)
High-Income/High-BHL*Time	0.00 (0.00)	0.01 (0.01)	0.01 (0.01)	0.01 (0.00)**
Intercept	1.42 (0.28)***	2.81 (0.41)***	4.23 (0.45)***	5.58 (0.59)***

Notes: Confidence intervals are in parentheses. *** $p<.01$, ** $p<.05$, * $p<.1$. Time defined as year/quarter. Adjusted for county level proportion of residents with more than four years of college education, county level unemployment rate, election year indicator and quarter fixed effects. BHL=Black and Hispanic/Latino.

Table 4 Quantile regression estimates reflecting the association between county income/BHL category and restaurant advertising expenditures, by restaurant type

	Lowest Density (Rural)	Low Density (Suburban-1)	Moderate Density (Suburban-2)	Highest Density (Urban)
Fast Food				
Low-Inc/High-BHL	1.36 (.21)***	1.16 (.31)***	0.56 (0.30)	0.08 (0.28)
Low-Inc/Low-BHL	0.00 (.03)	1.01 (.32)**	0.62 (0.39)	0.08 (0.38)
High-Inc/High-BHL	1.36 (.21)***	1.13 (.35)**	0.24 (0.32)	0.07 (0.25)
Time	0.00 (0.00)	-0.01 (.01)*	-0.01 (0.01)	-0.01 (0.01)
Low-Inc/High-BHL*Time	0.00 (0.00)	0.01 (.01)*	.02 (.00)***	.03 (.00)***
Low-Inc/Low-BHL*Time	-0.00 (0.00)	0.00 (0.00)	.01 (.00)**	.02 (.01)**
High-Inc/High-BHL*Time	-3.50 (0.00)***	0.00 (0.01)	.01 (.00)**	.02 (.00)***
Intercept	1.30 (.11)***	1.85 (.44)***	3.46 (0.39)***	4.75 (0.43)***
Fast Casual				
Low-Inc/High-BHL	-0.00 (0.01)	-0.01 (0.01)	0.02 (0.01)	-0.01 (0.02)***
Low-Inc/Low-BHL	-0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)	0.07 (0.01)
High-Inc/High-BHL	0.00 (0.01)	0.04 (0.01)**	0.02 (0.01)	0.66 (0.12)***
Time	0.00 (0.00)	0.00 (0.00)***	0.00 (0.00)**	0.00 (0.00)***
Low-Inc/High-BHL*Time	0.00 (0.00)	0.00 (0.00)**	0.00 (0.00)***	0.00 (0.00)***
Low-Inc/Low-BHL*Time	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)**
High-Inc/High-BHL*Time	0.00 (0.00)	0.00 (0.00)*	0.00 (0.00)	0.00 (0.00)***
Intercept	-0.03 (0.01)*	-0.08 (0.02)***	-0.09 (0.03)**	0.05 (0.04)
Full Service				
Low-Inc/High-BHL	0.25 (0.16)	0.10 (0.17)	0.08 (0.23)	0.74 (0.17)***
Low-Inc/Low-BHL	0.07 (0.12)	0.39 (0.20)	0.19 (0.15)	0.71 (0.35)*
High-Inc/High-BHL	-0.00 (0.18)	0.18 (0.23)	0.39 (0.19)*	-0.00 (0.00)
Time	0.00 (0.01)	0.00 (0.01)	-0.01 (0.00)**	-0.03 (0.00)***
Low-Inc/High-BHL*Time	-0.02 (0.01)	-0.00 (0.01)	0.00 (0.00)	-0.01 (0.00)*
Low-Inc/Low-BHL*Time	-0.00 (0.01)	-0.00 (0.01)	0.00 (0.00)	0.00 (0.00)
High-Inc/High-BHL*Time	0.01 (0.01)	-0.01 (0.01)	-0.00 (0.00)	-0.00 (0.00)
Intercept	0.89 (0.34)*	0.29 (0.19)	0.22 (0.24)	1.84 (0.30)***

Notes: Standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1. Time defined as year/quarter. Adjusted for county level proportion of residents with more than four years of college education, county level unemployment rate, election year indicator and quarter fixed effects. BHL = Black and Hispanic/Latino.

Supplementary A

Supplementary Table 1 Top-grossing restaurant chains (by restaurant type) from 2012-2016

Chain Type		
Fast-Food (N=49)	Fast Casual (N=17)	Full Serve (N=41)
7-Eleven	Boston Market	Applebee's
Arby's	Chipotle	BJ's Restaurant & Brewhouse
Auntie Anne's	Chuck E Cheese	Bob Evan's
Baskin Robbins	Cici's Pizza	Bonefish Grill
Bojangles	Corner Bakery	Buffalo Wild Wings
Burger King	Dickey's Barbecue Pit	California Pizza Kitchen
Captain D's Seafood	Jason's Deli	Capital Grille
Carl's Jr/Hardee's	Marco's Pizza	Carrabba's Italian Grill
Casey's General Store	Moe's Southwest Grill	Cheddar's
Checker's/Rally's	Noodles & Company	Cheesecake Factory
Chick-Fil-A	Panda Express	Chili's
Church's Chicken	Panera Bread	Cracker Barrel
Culver's	Papa Murphy's	Dave & Buster's
Dairy Queen	Potbelly	Denny's
Del Taco	Qdoba	Famous Dave's
Domino's	Round Table Pizza	Friendly's
Dunkin Donuts	Zaxby's	Frisch's/Bob's Big Boy
Einstein Bros		Golden Corral
El Pollo Loco		Hooters
Firehouse subs		IHOP
Five Guys		Joe's Crab Shack
In-N-Out Burger		Logan's Roadhouse
Jack in the Box		Longhorn Steakhouse
Jamba Juice		Maggiano's Little Italy
Jersey Mike's Subs		O'Charley's
Jimmy John's		Olive Garden
KFC		On the Border Mexican Cantina
Krispy Kreme		Outback Steakhouse
Krystal Restaurant		Perkins
Little Caesar's		PF Chang's
Long John Silver's		Pizza Hut
McAlister's Deli		Red Lobster
McDonald's		Red Robin
Papa John's		Romano's Macaroni Grill
Pollo Tropical		Ruby Tuesday
Popeye's		Ruth's Chris Steakhouse

Quizno's	Texas Roadhouse
Raising Cane's Chicken	TGI Friday's
Sbarro	Waffle House
Sheetz	Wingstop
Sonic	Yard House
Starbucks	
Steak N Shake	
Subway	
Taco Bell	
Tim Horton's	
Wendy's	
Whataburger	
White Castle	

Supplementary B: Description of Data Sources

AggData (restaurant locations):

Aggdata (www.aggdata.com) is a data service provider that provides the number and location of all chain restaurants in each US county. The data collected by Aggdata is updated every three months. Data was obtained from 2012 to 2016 for each of the 107 restaurant chains included in our analysis.

Nielsen Ad Intel (quarterly advertising spending):

Nielsen Ad Intel datasets include data on advertising expenditure at the Digital Marketing Area (DMA) level. This data is made available to our research team through a partnership with University of Chicago Booth School of Business, Kilts Center for Marketing. DMAs, developed by Nielsen Media Research, divide the U.S. into distinct groups of counties, which generally surround urban areas and receive the same advertising mediums. Restaurant advertising data for each chain includes cost, product description, the DMA where the advertisement was purchased, and media type (e.g., print, television, internet, radio). Data is released annually to researchers. Spending data was organized at the quarterly level consistent with the restaurant location data obtained from AggData. National advertising spending was evenly distributed across the 209 DMAs and added to the local spending reported at the DMA level.

American Community Survey (county-level characteristics):

County-level information about population characteristics (e.g., race/ethnicity) was obtained from the American Community Survey. The ACS is a continuous survey administered by the Census Bureau to a sample of approximately 2 million people each year. County-level information about the economic environment were obtained from the Census Small Area Income and Poverty Estimates and Bureau of Labor Statistics Local Area Unemployment data series.[50]