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Neighbourhood Convenience Stores and Childhood Weight Outcomes: An Instrumental Variable Approach

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The association between the commercial food environment and childhood obesity is increasingly assessed in the literature, but little is known about the role of convenience stores, an important food retail format worldwide. This study helps bridge the gap using individual-level data containing measured body mass index (BMI) for public schoolchildren and geo-coded residence and store locations in Arkansas, United States. The distance from residence to the nearest highway is employed to instrument neighborhood convenience store exposure, while controlling for possible confounding effects of other food stores. We find that exposure to at least one convenience store exposure is associated with a BMI z-score increase of 0.162 standard deviation, and exposure to each additional convenience store is associated with a BMI increase of 0.071 standard deviation. There is no evidence for a larger association among children from low-income families or those with limited access to healthy foods.

Keywords: convenience store; childhood; weight; obesity; instrumental variable, Arkansas

JEL codes: Q18, I18, D12

Introduction

Childhood obesity is a growing public health issue in the world (World Health Organization 2012). In the United States, nearly one in five children is now obese (Ogden et al. 2014), facing increasing risk for adulthood obesity and related health problems throughout lifetime (Serdula et al. 1993; Biro and Wien 2010). The prevalence of childhood obesity further translates into a substantial financial burden (with an annual estimation of 14.1 billion US dollars nationwide in prescription drug, emergency room and outpatient visit costs, see Trasande and Chatterjee 2009). Due to its significance, there have been urgent calls for a better understanding of obesogenic factors affecting children, which could assist the development, implementation and support of policy initiatives designed to address this issue (National Research Council 2010; Institute of Medicine 2012).

While body weight is clearly a product of numerous factors (e.g. see Ho et al. 2013; Morenga, Mallard, and Mann 2013; Kelley, Kelley, and Pate 2014 for recent systematic reviews), policies may be more effective if they target factors that are ubiquitous. One such factor is the commercial food environment. Existing studies have focused on supermarkets which provide healthy foods like fresh fruits and vegetables (e.g. Schafft, Jensen, and Hinrichs 2009; Thomsen et al., 2016), and have provided evidence that lack of access to healthy foods, as described by living in "food deserts", can increase the weight of school children. For example, Schafft, Jensen, and Hinrichs (2009) suggest each one point increase in the percentage of a district's population residing in a food desert is associated with a 0.044-0.060 percent increase in students risk or overweight. Thomsen et al. (2015) see that exposure to food deserts is associated with an average BMI z-score increase of 0.04 standard deviation. There is also evidence that proximity to fast-food restaurants (i.e. those providing minimal table services and offering energy dense food options) can increase bodyweight. Among numerous studies, Currie et al. (2010) report a fast-food restaurant within 0.1 miles (1 mile = 1.609 kilometres) of a school results in a 5.2 percent increase in obesity rates of children. Alviola et al. (2014) alternatively suggest that an addition of a fast-food restaurant within a one mile radius from a school is associated with 1.23% increase in school obesity rates.

While these findings are suggestive, there is a need to extend this literature to other pervasive store formats. Convenience stores are a major type of food retail outlet in the United States. They represent 5.5 percent of total food store sales in 2011, which, after grocery stores, constitutes the second largest market share among all food stores (United States Census Bureau 2011). Convenience stores tend to also have a larger proportion of energy-dense foods (Morland, Diez Roux, and Wing 2006). These foods are usually processed for ease of consumption, and sacrifice nutritional quality for convenience, including loss of fibre, vitamins, minerals, and phytonutrients and contain added sugars, fillers, preservatives, hydrogenated or saturated fats, sodium, artificial colours and flavours (Rosenkranz and Dzewaltowski 2008). Given that convenience foods are increasingly consumed at home (Nestle 2003; Kearney 2010; Smith, Ng, and Popkin 2013), and that neighborhood convenience store exposure is associated with low diet quality (Larson, Story, and Nelson 2009; Rummo et al. 2015), exposure to convenience stores could contribute to childhood obesity.

Convenience stores in the United States are also an interesting case because many of them have been approved to accept Supplemental Nutrition Assistance Program (SNAP, formerly Food Stamp Program) benefits. SNAP is a federal nutrition assistance program that provides an allotment of benefits for low-income people that can be redeemed for foods at participating retailers. Therefore, convenience stores that accept SNAP benefits may be an important source of foods for lower-income families, especially those with limited access to grocery stores. The ability to procure less healthy foods with SNAP benefits may help explain why SNAP benefits could result in unintended body weight gains (Chen, Yen, and Eastwood, 2005; Meyerhoefer and Pylypchuk, 2008). Convenience stores in this context are highly relevant to childhood obesity because 47 percent of SNAP recipients are children and over 70 percent of SNAP benefits go to households with children (Keith-Jennings 2012). Moreover, there is evidence that children from low-income households are vulnerable to unhealthy foods due to overeating and night eating (Dammann and Smith 2010), and convenience foods can play a substantial role in this regard. For these reasons, the association between convenience store exposure and the weight of children from low-income families could be disproportionately higher.

A few studies have examined the association between convenience stores and body weight, yet findings are inconsistent as some suggest significant weight increases (Morland, Diez Roux, and Wing 2006; Bodor et al. 2010), while others report no change (Wang et al. 2007; Morland and Evenson 2009). These studies focus on either adults or adolescents but not children. Also, none of them have explicitly considered the potential endogeneity (e.g., convenience store exposure is likely associated with certain unobserved characteristics that also affect weight and therefore bias the impact estimates). Moreover, most studies lack residence-specific distance-based measures of spatial access to food stores, which weakens empirical findings.

This study reassesses the relationship between convenience stores and weight gain during childhood using a unique individual-level dataset covering the population of public schoolchildren in Arkansas, United States, a state where the childhood obesity rate is among the highest in the country (Arkansas Center for Health Improvement 2010). Individual data are matched to food store locations around the children's residences and to neighborhood socioeconomic indicators. We construct different measures of convenience store exposure, including: 1) a binary measure indicating the existence of convenience store(s) within a specified radius of the child's residence, 2) the count of convenience stores within such radius, and 3) the distance from the child's home to the nearest convenience store. Given concerns about endogeneity, we use an instrumental variable approach, where the distance from the residence to the nearest highway is used as the excluded instrument. We further control for access to other food stores, namely fast-food restaurants and supermarkets, to minimize possible confounding effects.

We find that convenience store exposure is associated with a slight increase of body mass index (BMI) z-scores of schoolchildren. This result is consistent and robust to the use of alternative radii that define convenience store exposure. We further re-estimate our model using children from low-income families and those residing in areas with limited access to supermarkets, but find no evidence for a disproportionately larger association among these disadvantaged subgroups.

Our contribution is threefold. First, we provide the first population-wide evidence of the association between convenience store exposure and the body weight outcomes of children, and complement the growing literature on the commercial food environment and weight outcomes. Second, we provide robust results by explicitly considering confounding factors such as access to other food stores, and address concerns for possible heterogeneity among different population groups. Finally, the data we use have two distinct advantages. One is that BMI z-scores are based on measured (not self-reported), heights and weights of children, which is helpful as significant measurement errors in self-reported weight have been found (Cawley et al., 2015). The second advantage is in geographic precision. Our measures of convenience store exposure are based on the actual distance between the child's residential location and the store locations, thereby minimising any measurement error or inaccuracy and lending further credence to our findings.

Data

The current study is jointly facilitated by three datasets. The BMI health screening data of Arkansas public school children are from and maintained by the Arkansas Center for Health Improvement (ACHI). These data are administrative records collected by the Arkansas Department of Education in fulfilment of legislative mandate and maintained under contract with the Arkansas Department of Health for health surveillance initiatives. All individual records were anonymized and de-identified prior to analysis.

BMI measurements on all public school children in Arkansas began in 2003-2004 school year and have continued annually until 2006-2007 school year (BMI = weight in kilograms / (height in meters)^2). Beginning in the 2007-2008 school year, only children in even-numbered grades, kindergarten through tenth grade, have been measured. Although we have access to panel data from 2003-2010, we opted to use only the 2009-2010 school year to obtain a cross-section of students. A cross-sectional analysis is necessary given the instrumental variable strategy that we use here. Our instrumental variable, the distance from the child's home to the nearest highway, has limited temporal variation because highway locations are static and do not change with time. Thus temporal variation arises only when there is a change in the location of the child's residence. We selected the 2009-2010 school year because this is the most recent year in our sample. The 2009-2010 school year data include BMI measurements of schoolchildren in even numbered grades: kindergarten, grade 2, grade 4, grade 6, grade 8 and grade 10. Children's heights and weights were measured by trained personnel within each public school in Arkansas and were converted to age-gender-specific BMI z-scores according to the guidelines provided by the United States Centers for Disease Control and Prevention. The major advantage of these data is that they are based on exact measures instead of self-reported outcomes, and are implemented under the supervision of ACHI with statewide protocols to ensure uniformity in measurement procedures and equipment (Justus et al. 2007). In addition to BMI z-score, the data also provide information on the gender, age (in months), race, ethnicity and school lunch status (whether the child is eligible, based on family income, for free school lunch).

As the age range of the children in the full sample is quite large (from kindergarten to grade 10), full-sample estimation could mask possible age-related heterogeneity and therefore could be less meaningful for policy purposes. Consequently, we focus on younger children, aged less than 144 months (12 years), for three reasons. First, most children within this age range follow the development stage of adiposity rebound when increasing BMI after early childhood is generally observed (Boonpleng, Park, and Gallo, 2012). Understanding weight determinants at this stage is important. Second, as explained above, few studies have investigated the association between convenience store exposure and the weight outcomes of younger children, which is a knowledge gap to be filled. Third, the diets of younger children are more likely dictated by their caregivers, and possible association can be more accurately evaluated using the distance-based measures of store access. Older children are also important, yet they are more independent and more able to procure foods on their own volition. Studying the hypothesized relationship among older children is therefore beyond the capacity and scope of the current study.

Food store location data came from geo-coded business lists purchased from Dun and Bradstreet, Inc. (D&B). These data were commonly used in the literature to characterize food environments (e.g. Powell et al. 2007; Zick et al. 2009; Bader et al. 2010). Specifically, we use archival data for the year 2010 to match the BMI records. Convenience stores were identified based on the following standard industrial classification (SIC) codes: 5541(Gasoline Service Stations), 54110200 (Convenience Stores), and 54110202 (Convenience Stores, Independent). However, many convenience stores were contained within the general 5411 SIC code for Grocery Stores. Consequently, we inspected company names and/or trade names to verify the store format in this SIC code and identified additional convenience stores from this category. We also used Google street-view images to verify store formats.

Residential addresses of schoolchildren in the Arkansas BMI dataset were geo-coded by ACHI personnel, thereby allowing the measurement of convenience store exposure around each residence. Residences were further matched to a third data set, the 2009 American Community Survey (ACS) summary files. The 2009 ACS provides neighborhood-level demographic and socioeconomic statistics at census block group level. Using census defined places, we classified the residence of each child as either urban or rural based on his or her census block.

We construct several measures of convenience store exposure. First, we introduce a binary indicator that takes the value of one if there is at least one convenience store within a half mile of an urban residence or within two miles of a rural residence (otherwise it takes the value of zero). Second, we consider the counts of convenience stores within the half-mile and two-mile radii for urban and rural residences, respectively. Third, we measure the radial distance from the residence of each child to the nearest convenience store. The chosen radius cut-offs to define convenience store exposure are not arbitrary. Our data show that in urban areas, 22.43%, 51.42% and 85.24% of the observations have convenience store exposure within one quarter mile, one half mile, and one mile, while in rural areas, 19.80%, 40.98% and 81.02% of the observations have convenience store exposure within one mile, two miles, and five miles. Therefore, one half mile (urban) and two miles (rural) serve as reasonable midpoints for the sake of variation. That said, we also implement robustness check procedures using alternative radii.

While our focus is on the relationship between convenience stores and childhood body weight, we acknowledge that other features of the commercial food environment could also affect body weight outcomes. Analogous to convenience stores, we identified fast-food restaurants and supermarkets around the residence of each child using the D&B data. As in the classification of convenience stores, we used several sources of information to identify fast-food restaurants and supermarkets including SIC code, company name, trade name, and internet searches. Fast-food restaurants, as used in our study, include the major hamburger chains and drive-in restaurants (e.g., McDonalds, Burger King, Wendy's), dairy stores with large fast-food menus (e.g., Dairy Queen), quick-service taco formats (e.g., Taco Bell), and fried chicken restaurants (e.g., KFC, Chick-Fil-A). These fast-food restaurants exclude specialty stores such as ice-cream parlors not selling other fast-foods (e.g., Baskin-Robbins), coffee shops (e.g., Starbucks), and donut shops (e.g., Krispy Kream). A binary indicator of fast-food restaurant exposure is constructed based on the same radii of a half mile for urban residences and two miles for rural residences. We further identified food desert residences following Thomsen et al. (2015) who used criteria similar to USDA's Food Desert Atlas to classify a residence as a food desert if it was located in a low-income census block group and was more than one mile (ten miles) from the nearest supermarket in an urban (rural) census block. Low-income block groups are those with median household income less than 80 percent of the state median or at least 20 percent of the population below the poverty line.

Table 1 presents the descriptive statistics of variables. 47.8% of the children were exposed to neighborhood convenience stores within a half mile (two miles) in urban (rural) areas during the 2009-2010 school year. The average count of convenience stores within these radii was 0.920, about twice that of the exposure rate of 47.8%, suggesting that the exposed children faced roughly two stores on average. Fast-food restaurants were much less prevalent as only one quarter of all the children were exposed to fast-food restaurants within the same radius as used in convenience store measures. On the other hand, only nine percent of the total observations reflect children living in food deserts. Finally, the distance to nearest highway is highly skewed, as detailed below.

Methodology

Model specification

We specify and estimate the following linear regression model:

$$BMI_i = \beta_0 + \beta_1 D_i + \boldsymbol{\gamma X_i} + \boldsymbol{\delta C_i} + \epsilon_i \qquad (1)$$

where BMI_i is the BMI z-score of child i living in community c; D_i is the measure of convenience store exposure; $\boldsymbol{X_i}$ is a vector of individual characteristics with coefficients, $\boldsymbol{\gamma}$; $\boldsymbol{C_i}$ is a vector of community characteristics with coefficients, $\boldsymbol{\delta}$; and ϵ_i is the stochastic error. As discussed above, convenience store exposure measures include: 1) a binary indicator of convenience store existence within a half mile of an urban residence or within two miles of a rural residence, 2) the counts of convenience stores within these radii, and 3) the radial distance from the residence of each child to the nearest convenience store. On the other hand, $\boldsymbol{X_i}$ includes age, age squared, gender, race/ethnicity (two dummy indicators of African American and Hispanic), and a dummy indicator of free school lunch status. $\boldsymbol{C_i}$ includes a set of community characteristics from 2009 ACS files. Descriptive statistics of these variables are reported in Table 1.

Among all the coefficients, the one of primary interest is the marginal effect of convenience store exposure on BMI, measured by β_1. Direct estimates of β_1, however, may be inconsistent as convenience store exposure is likely endogenous for two reasons. On the one hand, household location decisions are based on numerous factors, some of which could be preferences for food healthfulness and access to certain foods. On the other hand, convenience stores are likely to choose locations that generate the highest profits. Therefore, convenience store exposure is not randomly assigned. It is for this reason that we consider an instrumental variable approach to address potential endogeneity. Specifically, we use distance from the residence to the nearest highway as the excluded instrument. Convenience stores usually cluster near highways to capture sales from traveling customers. This is evident in our data given that the distance to the nearest highway is highly skewed (mean: 1.686 miles; median: 0.318 miles; 75th percentile: 1.406 miles; skewness: 3.611), and the vast majority of convenience stores also sell gasoline. Empirically, we use interstate highways as well as United States numbered highway because the interstate system only serves a limited portion of Arkansas and the numbered highways are major arterial roads connecting population centres within the state (Alviola et al. 2014). Figure 1 presents the geographical distribution of convenience stores and highways in Arkansas in the studied year of 2010.

Instrument validity

Highway proximity has been successfully employed in the recent literature to identify the association between fast-food restaurants and weight outcomes (Dunn 2010; Anderson and Matsa 2011; Dunn et al., 2012; Alviola et al. 2014). These studies present extensive evidence in support of the validity of this instrument. Similarly, the appropriateness of highway proximity as the excluded instrument in the context of convenience store exposure needs to be carefully considered. As previously mentioned, we have access to panel data from 2003-2010. However, since few new US and Interstate highways were built in Arkansas from 2003-2010, there is no variation in this instrument from the construction of new highways over time. The only variation in the instrument came from schoolchildren who moved, but home relocation itself is also likely endogenous. Hence, we opt to follow existing studies to implement cross-sectional analysis (Dunn 2010; Anderson and Matsa 2011; Alviola et al. 2014), where the most recent school year data we have access to are used.

The foremost concern about our instrumental variable estimation is the existence of possible confounding effects. Fast-food restaurants and convenience stores provide highly similar (energy-dense) foods, and both types of stores tend to cluster along highways and each is potentially endogenous for similar reasons. Although convenience stores are far more ubiquitous than fast-food restaurants in Arkansas (see Table 1), there is still a need to account for the access to fast-food restaurants. Directly controlling for fast-food restaurant access, however, would lead to an empirical dilemma. On the one hand, models with multiple endogenous variables are difficult to identify, and the interpretation of simultaneous causalities is challenging. On the other hand, naïve inclusion of another possibly endogenous covariate as an 'exogenous' control is also problematic (Angrist and Pischke 2008). To avoid both pitfalls and appropriately identify the hypothesized effect, we first estimate our baseline model in equation (1) without controlling for fast-food restaurant access using the full sample. We then re-estimate the model using subsamples with or without fast-food restaurant access. If confounding effects exist, the estimated correlations with or without fast-food exposure should differ. We further apply a similar strategy to deal with food deserts. In results presented below, we find little meaningful difference in the estimates in either case.

In addition to potential confounders, another concern is the possibility of systematic differences among the characteristics of children living closer to and further away from highways that may also contribute to the estimates, thereby leading to biased results. For example, if children living closer to highways usually come from lower-income households, they may be heavier due to socio-economic disadvantages rather than increased exposure to convenience stores. To address this concern, we directly control for census-block level median household income using the 2009 ACS data. We also implement a series of OLS balancing test regressions where each explanatory variable is regressed against the instrument (e.g. Dunn 2010; Anderson and Matsa 2011; Alviola et al. 2014). Detailed results are presented in Appendix I. Although six of the 14 coefficient estimates are statistically significant, all coefficient magnitudes are extremely small. Therefore, this concern should be minimized.

Finally, the same instrument may not be equally valid for different subgroups of the population. For instance, health preferences and travel costs may differ by income status. Consequently, we separately analyse subsamples of children from low-income families and children living in food deserts. There is, however, no disproportionately higher correlation.

Empirical analysis

Our empirical analysis progresses as follows. We first implement the baseline estimation of equation (1) using the full sample. We then re-estimate the model using a variety of subsamples homogenized by the access to other store formats. Finally, we estimate the model using low-income and food-desert subsamples to assess whether a there is a higher correlation among the socioeconomically disadvantaged groups.

Baseline results

Table 2 presents our baseline results. Three specifications are estimated with alternative convenience store exposure measures as discussed above. First-stage results are presented in Appendix II.

The measure of convenience store exposure is statistically significant across all specifications. Specification (1) suggests that living close to neighborhood convenience store(s) is associated with a BMI z-score that is 0.162 standard deviations higher on average than those without such exposure. Specification (2) alternatively suggests that one more neighborhood convenience store is associated with a 0.071 standard deviation increase in BMI z-scores on average. Finally, specification (3) shows that a one-mile increase in the distance to the nearest convenience store reduces BMI z-score by 0.023 standard deviations.

Looking into the impact magnitudes, the coefficient estimate of convenience store exposure (0.162) is roughly twice the size of that of convenience store count (0.071). Given that about 47.8% of the children are exposed to convenience store(s) while the average number of convenience store(s) that they are exposed to is 0.920 (see Table 1), the above findings echo the latter fact that the average number of convenience stores for children exposed to at least one store is around two. Hence, in addition to convenience store exposure, the count of such stores also matters at the margin. In comparison, the coefficient of distance to the nearest convenience store is much smaller (0.023), and this is likely explained by the noticeable positive skewness of the distance measure (Table 1). Even so, it is still highly significant. These results consistently suggest that exposure to neighborhood convenience stores is associated with increased body weight outcomes of children.

Concerning the other covariates, African American and Hispanic children tend to be heavier. Also, children's BMI z-scores are negatively associated with community-level measures of income, higher education attendance, and proportion of working mothers (measuring women's empowerment), and positively associated with the proportion of households without vehicles. Most of these coefficient estimates, however, are much smaller than those of the convenience store measures.

The convenience store correlation we estimate is not large, but they need to be placed into some context. The average age in our sample is roughly 8.5 years. A girl of this age with a stature of 130 centimetres (roughly the centre of the height-for-age growth chart) and a weight of 29.8 kilograms would have a BMI z-score of 0.680, which is very close to the sample average. Our estimate of convenience store exposure in table 2 is 0.162 standard deviation. This translates into a weight gain for this child (assuming no change in stature or age) of 0.8 kilogram. To provide further context, the same girl would be classified as overweight (85th percentile of the distribution) if her weight were 31.6 kilograms, and she would be considered obese (95th percentile of the distribution) if her weight were 36.0 kilograms. In other words, a gain of 1.8 kilograms and 6.2 kilograms would move this child from her current status into the overweight category and the obese category, respectively. Therefore, our estimates, coupled with the aforementioned small expenditure share of food-store sales through convenience stores (5.5 percent in 2011), suggests that the possible role of these stores in childhood weight production and obesity should not be overlooked.

Robustness checks

We now turn to a series of procedures to check the robustness of these estimates against other possible obesogenic features in the commercial food environment and against heterogeneity in the socioeconomic status of children in the sample. We first check the possible confounding effects from fast-food restaurants using subsamples homogenized by access to fast-food restaurants. Possible effects from supermarkets are similarly addressed using subsamples homogenized by food desert status, which also helps us check whether the convenience store correlation of children in food deserts is disproportionately higher. To further investigate the possible income-related heterogeneity, we alternatively use the free school lunch status of each child, a good available proxy for family income, to homogenize samples by income status. According to the United States Office of Management and Budget, children qualify for free school lunch if household income is below 130% of the federal poverty threshold. Hence, we define a low-income subsample in terms of children that were qualified for free school lunches. Descriptive statistics of these subsamples are provided in Appendix III. It is seen that children without fast-food restaurant access within the above defined radii are also farther away from convenience stores and highways, and are living in better educated communities. On the other hand, children living in food deserts and those from lower income households tend to be heavier as measured by BMI z-scores. There are higher proportions of African American and Hispanic children among those groups, which also observe socioeconomic disadvantages in most observed characteristics. Most of these discrepancies are relatively small, yet they are statistically significant, implying a need to control for these covariates in regression modelling.

These results are presented in table 3. The first two panels of show results from the subsamples of children who were exposed to fast-food restaurants, and children who were not exposed to fast-food restaurants. The estimates across these two subsamples are almost identical and are very close to our main results, suggesting the robustness of the estimated association between convenience stores and BMI. These results are also intuitive because, 1) there are far fewer fast-food restaurants than convenience stores in our sample, and 2) fast-food restaurants only serve a limited variety of processed foods which are generally designed for immediate consumption. These types of foods could therefore play a smaller role as a source of daily foods in comparison to those available through convenience stores.

The third and fourth panels of Table 3 contain samples that are homogenized by food desert status. Again, there no meaningful difference across these subsamples (a discrepancy of 0.013 standard deviation in BMI z-scores means less than 0.1 kilogram weight difference for the representative girl discussed above). The estimates therefore suggest that children living in food-deserts did not show a disproportionately higher correlation between BMI and convenience store exposure. We speculate that, as food deserts are low-income neighbourhoods, price sensitivity can surpass convenience incentives and encourage people to obtain foods at lower prices from remote supermarkets even if they have easy access to neighborhood convenience stores. According to the 2009 ACS, only 5.36% of the residents of these communities did not own a vehicle and so transportation may not be an important barrier.

Estimates in the bottom panel of Table 3 further show that estimates from the subsample of children who were eligible for free school lunch are not meaningfully different. It is likely that many of the children in food deserts also qualify for free lunch. However, in comparison to the food-desert sample, there is a considerably larger number of children in subsample who qualified for free lunch. Thus, the free lunch subsample constitutes an alternative but broader subsample of children that were economically disadvantaged. Although it is widely argued that lower-income families are more vulnerable to unhealthy food environments, we do not see such associations in our results.

After confirming the robustness of the convenience store estimates to the presence of fast-food restaurants, the food desert status of children’s residences, and family income, we further check whether the convenience store estimates are affected by unobserved heterogeneity that would also in part explain total variation in BMI. Community-level characteristics not captured by the covariates as well as school characteristics (school food and health policy, school lunch quality, etc.) may require specific consideration in this regard. Consequently, we repeat the estimation using the full sample and the three alternative convenience store exposure measures but with neighborhood (census block group) fixed effects (instead of a vector of community characteristics, $\boldsymbol{C_i}$), with school fixed effects, and with both. Results are reported in Table

4. It is seen that changes in the estimates are rather small, which provides further evidence that the main results are robust.

A final robustness check concerns the radial distances used to define convenience store exposure. An argument can be made that the estimated association is local and might disappear quickly as the distance between the residence and the store increases. To address this, we re-estimate Specifications 1 and 2 using alternative radial distances between stores and residences. Specifically, these alternative distances include a more localized measure based on one quarter-mile (urban) and one-mile (rural) thresholds, and another less localized measures based on one-mile (urban) and five-mile (rural) thresholds. As shown in Table 5, although the estimates differ from those obtained under the baseline radial distance thresholds, they are still reasonably robust. As expected, closer distances to convenience stores leads to larger estimates, which reinforces the conclusion that exposure matters. That said, the estimates from the larger radius distances, while smaller, still appear to be of non-trivial magnitudes. All estimates continue to show statistical significance despite the largely reduced variation in these alternative measures of convenience store exposure.

Concluding remarks

We evaluate the association between neighborhood convenience store exposure and childhood BMI outcomes using a unique state-wide individual-level data set of Arkansas public schoolchildren containing exact BMI measures and distances between children’s residences and convenience stores. Our results confirm the hypothesized association and extend the literature on the relationship of commercial food environment and weight outcomes. While the correlation appears to be small, the exposure to such store(s) may translate into a weight gain that may not be trivial when considered in light of the small share of food expenditures received by these stores. These findings suggest that convenience stores may be one contributor to childhood obesity.

In defence of our empirical strategy, we conduct several tests to assess the appropriateness of using highway proximity as an instrumental variable. In addition, the estimated correlation is robust to presence of other obesogenic features of the food environment, socioeconomic status, certain unobserved heterogeneity and distances used to define convenience store exposure. The fact that there is no larger association among children from disadvantaged households is interesting and implies that the convenience store effects may be universal.

One limitation of our study is that we are unable to decipher the possible mechanisms linking convenience store exposure and weight outcomes with the current data that contain no information on actual dietary intakes. Also, given the census nature of the data, information beyond anthropometric measures is limited, and thus only one instrument is available through data merging. While this instrument has been successfully applied in food environment studies (Dunn 2010; Anderson and Matsa 2011; Dunn et al., 2012; Alviola et al. 2014), its validity relies critically on cross-sectional variation, and so this prevents us from estimating weight changes over time. Future studies should aim to address these issues by investigating the mechanisms through which convenience store exposure affects weight using alternative instruments that are appropriate for panel data analysis, and thus to provide additional important information for policy making.

Since childhood obesity has become a major concern in the United States and worldwide, understanding its association with neighborhood convenience stores on children is increasingly important. Admittedly, Arkansas is predominately rural and it may not be appropriate to generalize our findings too broadly to describe any other state. However, as childhood obesity rates are the highest among Southern states (Singh et al., 2008), our findings have some immediate implications to this hotspot. Regarding policy options, possible efforts can be made on both the demand and supply sides. For example, the Healthy Food Financial Initiative since the Obama Administration along with the "Let's Move" campaign led by the former First Lady utilise financial incentives to stimulate healthy food provision, including tax credits, grants and low-cost loans (Holzman, 2010; Qian et al., 2017). The USDA Fresh Fruit and Vegetable Program alternatively seeks to replace unhealthy snacks with fresh fruits and vegetables outside school hours (USDA Food and Nutrition Service, 2016). While our results do not justify the merits of these interventions, they help justify the need for such actions. Hence, along with existing studies suggesting increased consumption of convenience foods (Nestle 2003; Kearney 2010; Smith et al. 2013) and decreased diet quality over time (Larson, Story, and Nelson 2009; Rummo et al. 2015), our analysis calls for further investigation and policy attention on this issue.

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Appendix I: Coefficient estimates of OLS balancing tests

Table A1 presents the results of OLS balancing tests. Each line represents a separate regression where the dependent variable is a covariate included in vector $\boldsymbol{X_{it}}$ in equation (1), and the independent variable is the distance to the nearest highway.

Table A1. OLS balancing test results (n=89,612)1

Dependent variable	Coefficient (standard error)
Age	0.00005 (0.00005)
Age square	0.00000 (0.00002)
Female	0.00011 (0.00015)
African American	-0.00152 (0.00014)***
Hispanic	-0.00087 (0.00024)***
Free school lunch	-0.00001 (0.00001)
Median household income	0.00135 (0.00000)***
High school	0.00000 (0.00000)
Some college	0.00000 (0.00000)
College and above	-0.00001 (0.00000)***
Working mother	-0.00000 (0.00001)
Married household	0.00001 (0.00000)
Single-mother household	-0.00001 (0.00000)**
No vehicle	-0.00012 (0.00001)***

[1] Heteroskedasticity-robust standard errors are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Appendix II: First-stage estimation results

Table A2 presents the first-stage OLS results of main regressions in Table 2.

Table A2. First-stage regression results (n=89,612)[1, 2]

	Specification (1)	Specification (2)	Specification (3)
Distance to nearest highway	-0.113 (0.001)***	-0.046 (0.001)***	0.021 (0.003)***
Age	0.001 (0.000)*	0.002 (0.001)**	-0.002 (0.001)***
Age square	-0.000 (0.000)***	-0.000 (0.000)	0.000 (0.000)***
Female	0.007 (0.045)	0.016 (0.032)	0.033 (0.025)
African American	0.027 (0.008)***	0.021 (0.009)**	0.034 (0.012)***
Hispanic	0.009 (0.014)	0.036 (0.014)***	-0.020 (0.011)*
Free school lunch	-0.005 (0.002)	-0.004 (0.005)	-0.016 (0.011)
Median household income	-0.003 (0.000)***	-0.004 (0.000)***	0.003 (0.000)***
High school	0.067 (0.018)***	0.038 (0.015)**	-0.026 (0.015)*
Some college	-0.049 (0.021)**	-0.041 (0.006)***	-0.061 (0.068)
College and above	0.062 (0.029)**	-0.040 (0.047)	-0.034 (0.015)**
Working mother	-0.016 (0.005)***	0.013 (0.022)	-0.025 (0.017)
Married household	-0.027 (0.003)***	-0.038 (0.018)**	0.019 (0.006)***
Single-mother household	-0.044 (0.028)*	-0.062 (0.061)	0.016 (0.003)***
No vehicle	0.012 (0.000)***	0.009 (0.001)***	-0.015 (0.001)***
F statistic (*p*-value)	232.07 (0.000)	266.13 (0.000)	797.93 (0.000)

[1] The dependent variables in Specifications (1)-(3) are, respectively, the binary convenience store access measure with a half mile (urban) and two miles (rural), the count of convenience stores within the same radii, and the distance from the child's home to the nearest convenience store.

[2] Heteroscedasticity-robust standard errors are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Appendix III: Subsample descriptive statistics

Table A3 reports the descriptive statistics of the subsamples used in the robustness check procedure.

Table A3. Subsample descriptive statistics

	Children with fast-food restaurant access[1] *(n=21,865)*	Children without fast-food restaurant access[1] *(n=67,747)*	Children living in food deserts[2] *(n=7,975)*	Children living outside food deserts[2] *(n=81,637)*	Children with free school lunch status[3] *(n=38,354)*	Children without free school lunch status[3] *(n=51,258)*
BMI (z-score)	0.680 (1.093)	0.677 (1.084)	0.703 (1.133)	0.674 (1.095)**	0.688 (1.330)	0.672 (1.121)*
Convenience store exposure (1=yes; 0=no)	0.483 (0.566)	0.479 (0.536)	0.473 (0.559)	0.478 (0.524)	0.475 (0.520)	0.479 (0.515)
Convenience store count	0.935 (1.383)	0.916 (1.386)*	0.908 (1.696)	0.921 (1.402)	0.917 (1.541)	0.922 (1.437)
Convenience store distance (miles)	1.423 (2.217)	1.567 (2.164)***	1.564 (3.347)	1.555 (2.121)	1.553 (2.676)	1.556 (2.412)
Age (month)	103.1 (26.19)	103.2 (25.88)	103.0 (30.53)	103.2 (27.06)	103.2 (25.84)	103.2 (25.84)
Female (1=yes; 0=no)	0.498 (0.500)	0.498 (0.500)	0.499 (0.500)	0.498 (0.500)	0.498 (0.500)	0.498 (0.500)
African American (1=yes; 0=no)	0.223 (0.455)	0.211 (0.440)	0.252 (0.585)	0.209 (0.455)***	0.234 (0.534)	0.206 (0.442)***
Hispanic (1=yes; 0=no)	0.082 (0.102)	0.081 (0.100)	0.086 (0.116)	0.081 (0.101)***	0.081 (0.112)	0.080 (0.100)
Free school lunch (1=yes; 0=no)	0.424 (0.506)	0.430 (0.501)	0.447 (0.543)	0.426 (0.499)***	1.000 (0.000)	0.000 (0.000)***
Median household income (thousand USD)	40.86 (16.27)	40.77 (15.75)	37.78 (16.82)	41.01 (15.55)***	37.26 (17.12)	43.45 (15.51)***
High school (proportion)[4]	0.352 (0.124)	0.356 (0.111)***	0.345 (0.164)	0.356 (0.110)***	0.353 (0.132)	0.356 (0.128)**
Some college (proportion)[4]	0.213 (0.098)	0.215 (0.084)***	0.187 (0.108)	0.218 (0.115)***	0.204 (0.120)	0.212 (0.121)***
College and above (proportion)[4]	0.177 (0.160)	0.180 (0.142)**	0.135 (0.172)	0.183 (0.157)***	0.169 (0.160)	0.186 (0.145)***
Working mother (proportion)[5]	0.685 (0.221)	0.682 (0.220)*	0.663 (0.244)	0.685 (0.234)***	0.681 (0.222)	0.684 (0.219)**
Married household (proportion)[5]	0.720 (0.180)	0.722 (0.180)	0.713 (0.186)	0.722 (0.180)***	0.719 (0.183)	0.722 (0.181)*
Single-mother household (proportion)[5]	0.212 (0.166)	0.213 (0.168)	0.220 (0.172)	0.212 (0.166)***	0.234 (0.170)	0.206 (0.167)***
No vehicle (proportion)[6]	0.042 (0.048)	0.042 (0.046)	0.052 (0.047)	0.041 (0.047)***	0.044 (0.047)	0.041 (0.047)***
Fast-food restaurant exposure (1=yes; 0=no)	1.000 (0.000)	0.000 (0.000)***	0.238 (0.789)	0.245 (0.460)	0.240 (0.562)	0.246 (0.533)
Food desert (1=yes; 0=no)	0.086 (0.358)	0.090 (0.303)	1.000 (0.000)	0.000 (0.000)***	0.092 (0.333)	0.087 (0.319)**
Distance to nearest highway (mile)	1.481 (2.434)	1.760 (2.299)***	1.787 (2.551)	1.676 (2.238)***	1.694 (2.266)	1.680 (2.224)

[1] Fast-food restaurant access is defined as being exposed to at least one restaurant within a half mile for urban residences and two miles for rural residences.

[2] Food desert residences are those located in a low-income census block group (median household income less than 80 percent of the state median or at least 20 percent of the population below the poverty line) and is more than one mile (ten miles) from the nearest supermarket in an urban (rural) census block.

[3] Children qualify for free school lunch if household income is below 130% of the federal poverty threshold.

[4] Proportion among population over age 25 within the residence block group (from 2009 ACS).

[5] Proportion among all children under 18 within the residence block group (from 2009 ACS).

[6] Proportion among occupied housing units within the residence block group (from 2009 ACS).

Table 1. Descriptive statistics (n=89,612)

Variable	Mean	Std. Dev.	Min	Max
BMI (z-score)	0.678	1.082	-3.998	3.991
Convenience store exposure (1=yes; 0=no)	0.478	0.503	0.000	1.000
Convenience store count	0.920	1.373	0.000	26.00
Convenience store distance (miles)	1.556	2.095	0.002	26.42
Age (month)	103.2	25.84	53.33	144.0
Female (1=yes; 0=no)	0.498	0.500	0.000	1.000
African American (1=yes; 0=no)	0.213	0.432	0.000	1.000
Hispanic (1=yes; 0=no)	0.081	0.098	0.000	1.000
Free school lunch (1=yes; 0=no)	0.428	0.496	0.000	1.000
Median household income (thousand USD)	40.80	15.06	2.499	170.9
High school (proportion)[1]	0.355	0.109	0.000	1.000
Some college (proportion)[1]	0.215	0.073	0.000	0.632
College and above (proportion)[1]	0.179	0.131	0.000	1.000
Working mother (proportion)[2]	0.683	0.218	0.000	1.000
Married household (proportion)[2]	0.721	0.179	0.000	1.000
Single-mother household (proportion)[2]	0.213	0.162	0.000	1.000
No vehicle (proportion)[3]	0.042	0.046	0.000	0.459
Fast-food restaurant exposure (1=yes; 0=no)	0.244	0.460	0.000	1.000
Food desert (1=yes; 0=no)	0.089	0.296	0.000	1.000
Distance to nearest highway (mile)	1.686	2.122	0.000	27.48

[1] Proportion among population over age 25 within the residence block group (from 2009 ACS).

[2] Proportion among all children under 18 within the residence block group (from 2009 ACS).

[3] Proportion among occupied housing units within the residence block group (from 2009 ACS).

Table 2. Baseline instrumental variable regression results (n=89,612)[1]

	Specification (1)	Specification (2)	Specification (3)
Convenience store exposure[2]	0.162 (0.024)***		
Convenience store count[3]		0.071 (0.014)***	
Convenience store distance[4]			-0.023 (0.006)***
Age	-0.004 (0.004)	-0.005 (0.004)	-0.004 (0.004)
Age square	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Female	0.011 (0.015)	0.023 (0.015)	-0.007 (0.015)
African American	0.101 (0.013)***	0.106 (0.013)***	0.097 (0.014)***
Hispanic	0.059 (0.032)*	0.067 (0.032)**	0.064 (0.032)**
Free school lunch	0.003 (0.003)	0.002 (0.003)	0.003 (0.003)
Median household income[5]	-0.006 (0.003)**	-0.005 (0.003)**	-0.009 (0.003)***
High school[5]	0.015 (0.022)	0.018 (0.021)	0.020 (0.021)
Some college[5]	0.016 (0.019)	0.024 (0.019)	0.007 (0.019)
College and above[5]	-0.007 (0.003)**	-0.009 (0.003)***	-0.007 (0.003)**
Working mother[5]	-0.008 (0.004)*	-0.009 (0.004)**	-0.009 (0.004)**
Married household[5]	0.009 (0.026)	-0.005 (0.026)	-0.004 (0.026)
Single-mother household[5]	0.003 (0.019)	-0.007 (0.019)	-0.003 (0.019)
No vehicle[5]	0.001 (0.000)**	0.001 (0.000)***	0.001 (0.000)**
Endogeneity test[6]	168.17***	169.56***	155.79***
F-test of 1st stage excluded IV	1236.01***	1638.19***	2934.46***

[1] All specifications are estimated by two-stage least squares (2SLS). The dependent variable is BMI z-score in all specifications. Heteroscedasticity-robust standard errors are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

[2] Dummy indicator of convenience store presence within the half-mile (urban) or two-mile (rural) radius.

[3] The number of neighborhood convenience store(s) within the above-defined radius.

[4] The radial distance from the residence to the nearest convenience store.

[5] Neighborhood (census block group) level variables.

[6] GMM distance test statistic (with *p*-value) is reported.

Table 3. Robustness check against possible confounding effects[1]

	Specification (1)	Specification (2)	Specification (3)
Children with fast-food restaurant access (n=21,865)			
Convenience store exposure	0.157 (0.041)***		
Convenience store count		0.064 (0.021)***	
Convenience store distance			-0.020 (0.08)**
Children without fast-food restaurant access (n=67,747)			
Convenience store exposure	0.168 (0.027)***		
Convenience store count		0.075 (0.019)***	
Convenience store distance			-0.025 (0.008)***
Children living in food deserts (n=7,975)			
Convenience store exposure	0.171 (0.073)**		
Convenience store count		0.078 (0.038)**	
Convenience store distance			-0.020 (0.011)*
Children living outside food deserts (n=81,637)			
Convenience store exposure	0.159 (0.034)***		
Convenience store count		0.071 (0.017)***	
Convenience store distance			-0.024 (0.007)***
Children with free school lunch status (n=38,354)			
Convenience store exposure	0.170 (0.038)***		
Convenience store count		0.075 (0.022)***	
Convenience store distance			-0.018 (0.008)**
Children without free school lunch status (n=51,258)			
Convenience store exposure	0.160 (0.026)***		
Convenience store count		0.066 (0.017)***	
Convenience store distance			-0.027 (0.015)*

[1] All specifications are estimated by two-stage least squares (2SLS). The dependent variable is BMI z-score in all specifications. Heteroscedasticity-robust standard errors are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table 4. Robustness check against unobserved heterogeneity[1]

	Specification (1)	Specification (2)	Specification (3)
With neighborhood fixed effects only			
Convenience store exposure	0.154 (0.027)***		
Convenience store count		0.066 (0.021)***	
Convenience store distance			-0.021 (0.011)**
With school fixed effects only			
Convenience store exposure	0.147 (0.033)***		
Convenience store count		0.065 (0.022)***	
Convenience store distance			-0.017 (0.007)**
With neighborhood and school fixed effects			
Convenience store exposure	0.153 (0.044)***		
Convenience store count		0.062 (0.027)**	
Convenience store distance			-0.019 (0.009)**

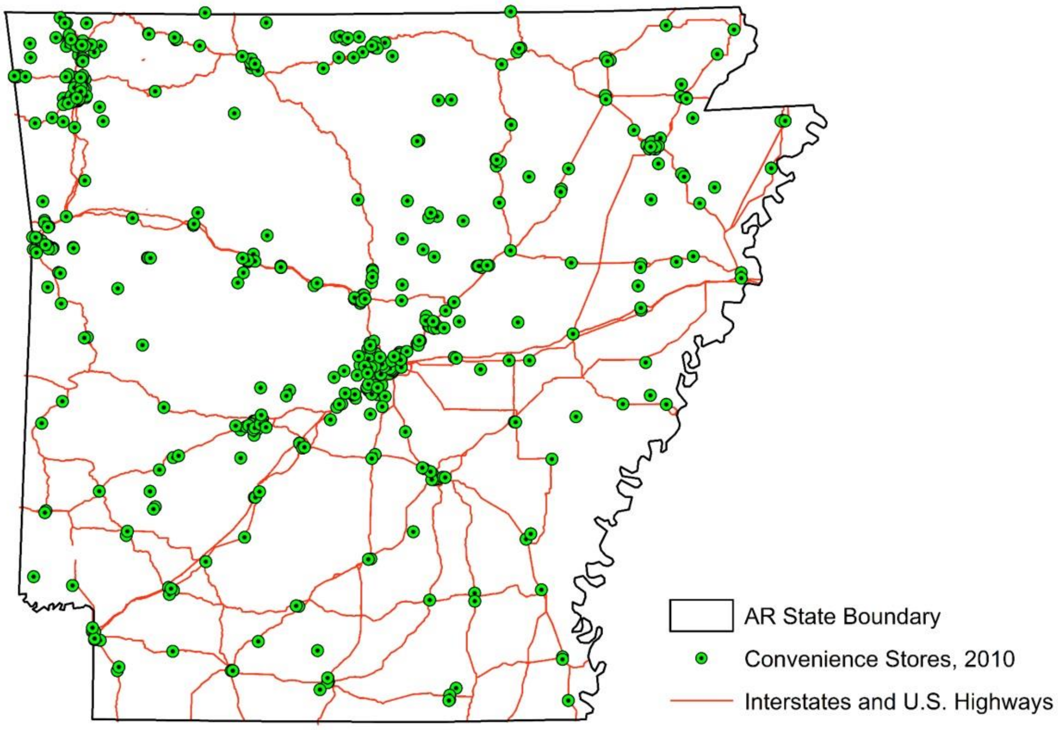
[1] All specifications are estimated by two-stage least squares (2SLS). The dependent variable is BMI z-score in all specifications. Heteroscedasticity-robust standard errors are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Table 5. Robustness check with alternative radii (n=89,612)[1, 2]

	Specification (1)	Specification (2)
One quarter mile (urban) and one mile (rural)		
Convenience store dummy	0.249 (0.031)***	
Convenience store count		0.114 (0.019)***
One mile (urban) and five miles (rural)		
Convenience store dummy	0.073 (0.037)**	
Convenience store count		0.034 (0.016)**

[1] All specifications are estimated by two-stage least squares (2SLS). The dependent variable is BMI z-score in all specifications. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, *** indicate statistical significance at 10%, 5% and 1% levels, respectively.

Figure 1. Convenience store location in Arkansas, United States (2010)[1]



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[1] Mapped with geocoded data from Dun & Bradstreet (D&B) business lists, 2010.