American Economic Journal: Economic Policy 2 (August 2010): 32–63
http://www.aeaweb.org/articles.php?doi=10.1257/pol.2.3.32

The Effect of Fast Food Restaurants on Obesity and Weight Gain†

By Janet Currie, Stefano DellaVigna, Enrico Moretti, and Vikram Pathania*

We investigate how changes in the supply of fast food restaurants affect weight outcomes of 3 million children and 3 million pregnant women. Among ninth graders, a fast food restaurant within 0.1 miles of a school results in a 5.2 percent increase in obesity rates. Among pregnant women, a fast-food restaurant within 0.5 miles of residence results in a 1.6 percent increase in the probability of gaining over 20 kilos. The implied effects on caloric intake are one order of magnitude larger for children than for mothers, consistent with smaller travel cost for adults. Non-fast food restaurants and future fast-food restaurants are uncorrelated with weight outcomes. (*JEL* I12, J13, J16, L83)

In the public debate over obesity it is often assumed the widespread availability of fast food restaurants is an important determinant of obesity rates. Policy makers in several cities have responded by restricting the availability or content of fast food, or by requiring posting of the caloric content of the meals (Julie Samia Mair, Matthew W. Pierce, and Stephen P. Teret 2005).[1] But the evidence linking fast food and obesity is not strong. Much of it is based on correlational studies in small data sets.

In this paper we seek to identify the effect of increases in the local supply of fast food restaurants on obesity rates. Using a new dataset on the exact geographical location of restaurants, we ask how proximity to fast food restaurants affects the obesity rates of over 3 million school children and the weight gain of 3 million

* Currie: Department of Economics, Columbia University, 420 W 118th St, New York, NY 10027 (e-mail: janet.currie@columbia.edu); DellaVigna: Department of Economics, University of California at Berkeley, 549 Evans Hall #3880, Berkeley, CA 94720-3880 (e-mail: sdellavi@berkeley.edu); Moretti: Department of Economics, University of California at Berkeley, 549 Evans Hall #3880, Berkeley, CA 94720-3880 (e-mail: moretti@econ.berkeley.edu); Pathania: Cornerstone Research, 353 Sacramento Street, 23rd Floor, San Francisco, CA 94111 (e-mail: pathania@econ.berkeley.edu). The authors thank John Cawley, two anonymous referees, and participants in seminars at the National Bureau of Economic Research Summer Institute, the 2009 AEA Meetings, the ASSA 2009 Meetings, the Federal Reserve Banks of New York and Chicago, the Federal Trade Commission, the New School, the Tinbergen Institute, University of California at Davis, the Rady School at University of California at San Diego, and Williams College for helpful comments. We thank Joshua Goodman, Cecilia Machado, Emilia Simeonova, Johannes Schmeider, and Xiaoyu Xia for excellent research assistance. We thank Glenn Copeland of the Michigan Department of Community Health, Katherine Hempstead and Matthew Weinberg of the New Jersey Department of Health and Senior Services, and Rachelle Moore of the Texas Department of State Health Services for their help in accessing the data. The authors are solely responsible for the use that has been made of the data and for the contents of this article.

† To comment on this article in the online discussion forum, or to view additional materials, visit the articles page at http://www.aeaweb.org/articles.php?doi=10.1257/pol.2.3.32.

[1] Tami Abdollah. "A Strict Order for Fast Food," *Los Angeles Times*, A-1, Sept. 10, 2007, http://articles.latimes.com/2007/sep/10/local/me-fastfood10. See also Sarah McBride. "Exiling the Happy Meal," *Wall Street Journal*, July 22, 2008, http://online.wsj.com/article/SB121668254978871827.html (Accessed on Nov. 9, 2009).

pregnant women. For school children, we observe obesity rates for ninth graders in California over several years, and we are therefore able to estimate models with and without school fixed effects. For mothers, we employ the information on weight gain during pregnancy reported in the Vital Statistics data for Michigan, New Jersey, and Texas covering 15 years. We focus on women who have at least two children so that we can follow a given woman across two pregnancies.

The design employed in this study allows for a more precise identification of the effect of fast food restaurants on obesity than the previous literature. First, we observe information on weight for millions of individuals compared to at most tens of thousand in the standard datasets used previously. This large sample size substantially increases the power of our estimates. Second, we exploit very detailed geographical location information, including distances of only one-tenth of a mile. By comparing groups of individuals who are at only slightly different distances to a restaurant, we can arguably diminish the impact of unobservable differences in characteristics between the groups. Since a fast food restaurant's location might reflect characteristics of the area, we test whether there are any observable patterns in restaurant location within the very small areas we focus on. Third, we have a more precise idea of the timing of exposure than many previous studies. The ninth graders are exposed to fast food restaurants near their new school from September until the time of a spring fitness test, while weight gain during pregnancy pertains to the nine months of pregnancy.

While it is clear that fast food is often unhealthy, it is not obvious a priori that changes in the proximity of fast food restaurants should be expected to have an impact on health. On the one hand, it is possible that proximity to a fast food restaurant simply leads to substitution away from unhealthy food prepared at home or consumed in existing restaurants, without significant changes in the overall amount of unhealthy food consumed. On the other hand, proximity to a fast food restaurant could lower the monetary and nonmonetary costs of accessing unhealthy food.[2]

Ultimately, the effect of changes in the proximity of fast food restaurants on obesity is an empirical question. We find that among ninth-grade children, the presence of a fast food restaurant within one-tenth of a mile of a school is associated with an increase of about 1.7 percentage points in the fraction of students in a class who are obese relative to the presence of a fast food restaurant at 0.25 miles. This effect amounts to a 5.2 percent increase in the incidence of obesity among the affected children. Since grade 9 is the first year of high school and the fitness tests take place in the spring, the period of fast food exposure that we measure is approximately 30 weeks, implying an increased caloric intake of 30 to 100 calories per school-day. We view this as a plausible magnitude. The effect is larger in models that include school fixed effects. Consistent with highly nonlinear transportation costs, we find no discernable effect at 0.25 miles and at 0.5 miles.

Among pregnant women, we find that a fast food restaurant within a half mile of a residence results in a 0.19 percentage point higher probability of gaining over 20 kilograms (kg). This amounts to a 1.6 percent increase in the probability of gaining

[2] In addition, proximity to fast food may increase consumption of unhealthy food even in the absence of any decrease in cost if individuals have self-control problems.

over 20 kilos. The effect increases monotonically and is larger at 0.25, and larger still at 0.1 miles. The increase in weight gain implies an increased caloric intake of one to four calories per day in the pregnancy period. The effect varies across races and educational levels. It is largest for African American mothers and for mothers with a high school education or less. It is zero for mothers with a college degree or an associate's degree.

Our findings suggest that increases in the supply of fast food restaurants have a significant effect on obesity, at least for some groups. On the other hand, our estimates do not suggest that proximity to fast food restaurants is a major determinant of obesity. Calibrations based on our estimates indicate that increases in the proximity of fast food restaurants can account for 0.5 percent of the increase in obesity among ninth graders over the past 30 years, and for at most 2.7 percent of the increase in obesity over the past 10 years for all women under 34. This estimate for mothers assumes other women in that age range react similarly to pregnant women; if they react less, then it is an upper bound.

Our estimates seek to identify the health effect of changes in the *supply* of fast food restaurants. However, it is, in principle, possible that our estimates reflect unmeasured shifts in the *demand* for fast food. Fast food chains are likely to open new restaurants where they expect demand to be strong, and higher demand for unhealthy food is almost certainly correlated with higher risk of obesity. The presence of unobserved determinants of obesity that may be correlated with increases in the number of fast food restaurants would lead us to overestimate the role of fast food restaurants.

We cannot entirely rule out this possibility. However, four points lend credibility to our interpretation. First, our key identifying assumption for mothers is that, in the absence of a change in the local supply of fast food, mothers would gain a similar amount of weight in each pregnancy. Given that we are looking at the *change* in weight *gain* for the same mother, this assumption seems credible. Our key identifying assumption for schools is that, in the absence of a fast food restaurant, schools that are 0.1 miles from a fast food restaurant and schools that are 0.25 miles from a fast food restaurant would have similar obesity rates.[3]

Second, while current proximity to a fast food restaurant affects current obesity rates, proximity to *future* fast food restaurants, controlling for current proximity, has no effect on current obesity rates and weight gains.

Third, while proximity to a fast food restaurant is associated with increases in obesity rates and weight gains, proximity to non-fast food restaurants has no discernible effect on obesity rates or weight gains. This suggests that our estimates are not just capturing increases in the local demand for restaurant establishments, or other characteristics of the neighborhood that might be correlated with a high density of restaurants.

[3] This assumption may appear problematic given previous research (S. Bryn Austin et al. 2005) which suggests that fast food restaurants are more prevalent within 1.5 miles of a school. However, we only require that, *within a quarter of a mile from a school,* the exact location of a new restaurant opening is determined by idiosyncratic factors such as where suitable locations become available.

Finally, we directly investigate the extent of selection on observables. We find that observable characteristics of schools are not associated with changes in the availability of a fast food restaurant in the immediate vicinity of a school. Fast food restaurants are equally likely to be located within 0.1, 0.25, and 0.5 miles of a school. Also, the observable characteristics of mothers that predict large weight gains are negatively, not positively, related to the presence of a fast food chain, suggesting that any bias in our estimates for mothers may be downward, not upward. Taken together, the weight of the evidence is consistent with a causal effect of fast food restaurants on obesity rates among ninth graders and on weight gains among pregnant women.

The estimated effects of proximity to fast food restaurants on obesity are consistent with a model in which access to fast food restaurants increases obesity by lowering food prices or by tempting consumers with self-control problems.[4] Differences in travel costs between students and mothers could explain the different effects of proximity. Ninth graders have higher travel costs in the sense that they are constrained to stay near the school during the school day, and hence are more affected by fast food restaurants that are very close to the school. For this group, proximity to a fast food restaurant has a quite sizeable effect on obesity. In contrast, for pregnant women, proximity to a fast food restaurant has a quantitatively small (albeit statistically significant) impact on weight gain. Our results suggest that concerns about the effects of fast food restaurants in the immediate proximity of schools are well-founded. Although relatively few students are affected, these restaurants have a sizeable effect on obesity rates among those who are affected.

The remainder of the paper is organized as follows. In Section I, we review the existing literature. In Section II, we describe our data sources. In Section III, we present the econometric models. In Sections IV and V, we present the empirical findings for students and mothers, respectively. In Section VI, we discuss policy implications and conclude.

I. Background

While there is considerable evidence in the epidemiological literature of correlation between fast food consumption and obesity, it has been more difficult to demonstrate a causal role for fast food. A recent review about the relationship between fast food and obesity (R. Rosenheck 2008) concludes that “Findings from observational studies as yet are unable to demonstrate a causal link between fast food consumption and weight gain or obesity.”

A rapidly growing economics literature has focused on the link between declining food prices and obesity (see Tomas Philipson and Richard Posner 2008 for a review).[5] A series of recent papers explicitly focus on fast food restaurants as poten-

[4] See DellaVigna (2009). A model of cues in consumption (David Laibson 2001) has similar implications: a fast food restaurant that is in immediate proximity from the school is more likely to trigger a cue that leads to over-consumption.

[5] For example, Darius Lakdawalla and Philipson (2002) argue that about 40 percent of the increase in obesity from 1976 to 1994 is attributable to lower food prices. Charles Courtemanche and Art Carden (2008) examine the

tial contributors to obesity.[6] The two papers closest to ours are Michael Anderson and David A. Matsa (2009) and Brennan Davis and Christopher Carpenter (2009). Anderson and Matsa (2009) focus on the link between eating out and obesity using the presence of Interstate highways in rural areas as an instrument for restaurant density. They find no evidence of a causal link between restaurants and obesity.

Our paper differs from Anderson and Matsa (2009) in three important dimensions, and these differences are likely to explain the discrepancy in our findings. First, we have a very large sample that allows us to identify even small effects. Our estimates of weight gain for mothers are within the confidence interval of Anderson and Matsa's (2009) two-stage least squares estimates. Second, we have the *exact* location of each restaurant, school, and mother. In contrast, Anderson and Matsa (2009) use telephone exchanges as the level of geographical analysis. Given our findings, it is not surprising that at their level of aggregation the estimated effect is zero. Third, the populations under consideration are different. Anderson and Matsa (2009) focus on predominantly white rural communities, while the bulk of both the ninth graders and the mothers we examine are urban and many of them are minorities. We show that the effects vary considerably depending on race. Indeed, when Richard A. Dunn (2008) uses an instrumental variables approach similar to the one used by Anderson and Matsa (2009), he finds no effect for rural areas or for whites in suburban areas, but strong effects for blacks and Hispanics. As we show below, we also find stronger effects for minorities.

Davis and Carpenter (2009) use individual-level student data from the California Healthy Kids Survey. In contrast to our study, Davis and Carpenter (2009) present only cross-sectional estimates, and pool data from grades 7–12. They focus on fast food restaurants within 0.5 miles of a school, although they also present results for within 0.25 miles of a school. Their main outcome measure is BMI, which is computed from self-reported data on height and weight. Relative to their study, our study adds longitudinal estimates, the focus on ninth graders, a better obesity measure, estimates for pregnant mothers, and checks for possible unobserved differences between people and schools located near fast food restaurants and others.

II. Data and Summary Statistics

Data for this project come from three sources: school data, mothers data, and restaurant data.

impact on obesity of Walmart and warehouse club retailers such as Sam's club, Costco, and BJ's wholesale club which compete on price.

[6] Shin-Yi Chou, Michael Grossman, and Henry Saffer (2004) estimate models combining state-level price data with individual demographic and weight data from the Behavioral Risk Factor Surveillance surveys and find a positive association between obesity and the per capita number of restaurants (fast food and others) in the state. Inas Rashad, Grossman, and Chou (2006) present similar findings using data from the National Health and Nutrition Examination Surveys. Patricia M. Anderson and Kristin F. Butcher (2005) investigate the effect of school food policies on the body mass index (BMI) of adolescent students. Anderson, Butcher, and Phillip B. Levine (2003) find that maternal employment is related to childhood obesity, and speculate that employed mothers might spend more on fast food. John Cawley and Feng Liu (2007) show that employed mothers spend less time cooking. Raphael Thomadsen (2001) estimate a discrete choice model of supply and demand that links prices to market structure and geographical dispersion of fast food outlets in California.

A. *School Data*

Data on children comes from the California public schools for the years 1999 and 2001–2007. The observations for ninth graders, which we focus on in this paper, represent 3.06 million student-year observations. In the spring, California ninth graders are given a fitness assessment, the FITNESSGRAM®. Data are reported at the class level in the form of the percentage of students who are in the "healthy fitness zone" with regard to body fat, and who have acceptable levels of abdominal strength, aerobic capacity, flexibility, trunk strength, and upper body strength. Data are available only for cell sizes with greater than 10 students, so that for some of the subgroup analyses we report below, there are some cells with data that are suppressed. What we will call obesity is the fraction of students whose body fat measures are outside the healthy fitness zone. For boys, this means that they have body fat measures greater than 25 percent, while for girls, it means that they have body fat measures greater than 32 percent. Body fat is measured using skin-fold calipers and two skinfolds (calf and triceps). This way of measuring body fat is considerably more accurate than the usual BMI measure (Cawley and Burkhauser 2008). Since grade nine is the first year of high school and the fitness tests take place in the spring, this impact corresponds to approximately 30 weeks of fast food exposure.[7,8]

B. *Mothers Data*

Data on mothers come from Vital Statistics Natality data from Michigan, New Jersey, and Texas. These data are from birth certificates, and cover all births in these states from 1989 to 2003 (from 1990 in Michigan). Confidential data including mothers names, birth dates, and addresses, were used to construct a panel dataset linking births to the same mother over time, and then to geocode her location (again using ArcView).[9] The Vital Statistics Natality data are very rich, and include information about the mother's age, education, race and ethnicity; whether she smoked during pregnancy; the child's gender, birth order, and gestation; whether it was a multiple birth; and maternal weight gain. We restrict the sample to singleton births and to mothers with at least two births in the sample, for a total of over 3.5 million births.

[7] In very few cases, a high school is in the same location as a middle school, in which case the estimates reflect a longer term impact of fast food.

[8] This administrative dataset is merged to information about schools (including the percent black, white, Hispanic, and Asian, percent immigrant, pupil/teacher ratios, fraction eligible for free lunch, etc.) from the National Center for Education Statistic's Common Core of Data, as well as Standardized Testing and Reporting (Star) test scores for the ninth grade. The location of the school was geocoded using ArcView. Finally, we merged in information about the nearest census block group of the school from the 2000 census including the median earnings, percent high school degree, percent unemployed, and percent urban.

[9] In Michigan, the state created the panel and gave us de-identified data with latitude and longitude. In New Jersey, the matching was done at the state offices and then we used de-identified data. The importance of maintaining confidentiality of the data is one reason we do not use continuous distance measures in the paper.

C. *Restaurant Data*

Restaurant data with geo-coded information come from the National Establishment Time Series Database (Dun and Bradstreet). These data are used by all major banks, lending institutions, insurance companies, and finance companies as the primary system for creditworthiness assessment of firms. As such, it is arguably more precise and comprehensive than yellow pages and business directories.[10] We obtained a panel of virtually all firms in Standard Industrial Classification 58 ("Eating and Drinking Places") from 1990 to 2006, with names and addresses. Using this data, we constructed several different measures of fast food restaurants and other restaurants, as discussed further in Appendix 1. In this paper, the benchmark definition of fast food restaurants includes only the top 10 fast food chains in the country, namely, McDonalds, Subway, Burger King, Taco Bell, Pizza Hut, Little Caesars, KFC, Wendy's, Domino's Pizza, and Jack in the Box. We also show estimates using a broader definition that includes both chain restaurants and independent burger and pizza restaurants. Finally, we also measure the supply of non-fast food restaurants. The definition of these "other restaurants" changes with the definition of fast food. Table 1A in the Appendix lists the top 10 fast food chains as well as examples of restaurants that we did not classify as fast food.

Matching was performed using information on latitude and longitude of restaurant location. Specifically, we match the schools and mother's residence to the closest restaurants using ArcView software. For the school data, we match the results on testing for the spring of year t with restaurant availability in year $t-1$. For the mother data, we match the data on weight gain during pregnancy with restaurant availability in the year that overlaps the most with the pregnancy.

Summary Statistics.—Using the data on restaurant, school, and mother's locations, we constructed indicators for whether there was a fast food restaurant or other restaurant within 0.1, 0.25, and 0.5 miles of either the school or the mother's residence. Table 1A shows summary characteristics of all the controls variables in the schools dataset by distance to a fast food restaurant, where distances are overlapping. Here, as in most of the paper, we use the narrow definition of fast food, including the top-10 fast food chains. Only 7 percent of schools have a fast food restaurant within 0.1 miles, while 65 percent of all schools have a fast food restaurant within one-half mile.[11] Schools within 0.1 miles of a fast food restaurant have more Hispanic students and lower test scores. They are also located in poorer and more urban areas. The last row indicates that schools near a fast food restaurant have a higher incidence of obese students than the average California school. Table 1B shows a similar summary of the mother data, indicating all the control variables. Again, mothers who live very near fast food restaurants have different

[10] The yellow pages are not intended to be a comprehensive listing of businesses. They are a paid advertisement. Companies that do not pay are not listed.

[11] The average school in our sample had 4 fast food restaurants within 1 mile and 24 other restaurants within the same radius.

Table 1A—Summary Statistics for California School Data

	All	< 0.5 miles FF	< 0.25 miles FF	< 0.1 miles FF
Number of school-year observations	8,373	5,188	2,321	559
Number of students in ninth grade	366.27	384.30	383.05	400.74
School characteristics				
School qualified for Title I funding	0.397	0.411	0.406	0.436
Number of students	1,566.184	1,663.978	1,663.624	1,715.707
Student teacher ratio	22.393	22.841	22.668	22.857
Share black students	0.084	0.093	0.093	0.086
Share Asian students	0.107	0.117	0.118	0.116
Share Hispanic students	0.380	0.409	0.416	0.436
Share Native American students	0.014	0.010	0.010	0.012
Share immigrant students	0.034	0.029	0.030	0.033
Share female students	0.475	0.477	0.477	0.490
Share eligible for free lunch	0.290	0.306	0.313	0.311
Share eligible for subsidised lunch	0.063	0.064	0.063	0.063
FTE teachers per student	0.048	0.047	0.047	0.047
Average test scores for ninth grade	56.255	54.964	54.737	52.291
Test score information missing	0.024	0.020	0.022	0.016
School district characteristics				
Student teacher ratio	20.897	21.095	20.911	21.092
Share immigrant students	0.028	0.025	0.025	0.028
Share non-English speaking (LEP/ELL) students	0.206	0.224	0.225	0.222
Share IEP students	0.126	0.125	0.132	0.120
Staff student ratio	0.102	0.099	0.102	0.095
Share diploma recipients	0.086	0.084	0.082	0.091
Share diploma recipients missing	0.004	0.004	0.008	0.000
2000 Census Demographics of nearest block				
Median household income	48,596	45,687	44,183	44,692
Median earnings	25,674	24,668	24,271	23,942
Average household size	2.97	2.93	2.84	2.88
Median contract rent for rental units	743.74	741.19	734.14	706.29
Median gross rent for rentals units	835.74	825.46	812.54	781.93
Median value for owner-occupied housing	202,783	199,824	199,834	195,244
Share white	0.629	0.597	0.591	0.578
Share black	0.056	0.062	0.064	0.053
Share Asian	0.090	0.099	0.098	0.110
Share male	0.491	0.489	0.487	0.494
Share never married	0.289	0.310	0.320	0.314
Share married	0.546	0.519	0.505	0.513
Share divorced	0.103	0.107	0.111	0.107
Share high school degree only	0.220	0.219	0.219	0.220
Share some college	0.235	0.226	0.223	0.219
Share Associate degree	0.072	0.069	0.071	0.072
Share Bachelor's degree	0.150	0.149	0.151	0.139
Share graduate degree	0.078	0.076	0.077	0.069
Share in labor force	0.616	0.618	0.619	0.617
Share unemployed	0.083	0.085	0.088	0.079
Share with household income <$10K	0.092	0.099	0.106	0.101
Share with household income >$200K	0.026	0.022	0.020	0.020
Share with wage or salary income	0.782	0.784	0.784	0.789
Share of housing units occupied	0.946	0.953	0.953	0.950
Share in owner-occupied units	0.592	0.530	0.481	0.488
Share urban	0.912	0.974	0.971	0.987
Outcome				
Percent obese students	32.949	33.772	33.724	35.733

Note: This table lists all the controls used for the school regressions, with the exception of year and school fixed effects.

Table 1B—Summary Statistics for Birth Data

	All births	Siblings only	Siblings ≦ 0.5 mile	Siblings ≦ 0.25 mile	Siblings ≦ 0.1 mile
Number of mother-year observations	5,683,798	3,019,256	835,798	258,707	44,828
Demographic characteristics					
Age of mother	26.975	26.772	26.450	26.249	25.963
Mother graduated from high school	0.320	0.310	0.312	0.315	0.314
Mother attended some college	0.332	0.333	0.301	0.288	0.268
Mother attended college or more	0.079	0.077	0.065	0.059	0.050
Mother is black	0.156	0.164	0.196	0.195	0.202
Mother is hispanic	0.278	0.263	0.309	0.324	0.348
Mother is smoking	0.107	0.107	0.108	0.111	0.111
Child is male	0.512	0.512	0.512	0.511	0.507
Parity	1.016	1.180	1.200	1.190	1.180
Mother is married	0.687	0.696	0.651	0.639	0.623
Other control variables are: (i) indicators for single year of age of the mother, (ii) indicators for year of birth, (iii) indicator for missing variables: education, race, smoking, gender, parity, marital status.					
Outcomes					
Weight gain greater than 20 kg	0.126	0.118	0.120	0.121	0.123
Weight gain greater than 15 kg	0.364	0.352	0.349	0.350	0.351
Weight gain (in kg)	13.664	13.491	13.410	13.412	13.400

Notes: There are 1,527,328 mothers with greater than or equal to two children in the full sample. There are 3,262 zip codes. Also, 412,829 mothers experience a change in fast food availability within 0.5 miles, 181,250 experience such a change within 0.25 miles, and 37,976 experience a change within 0.1 miles.

characteristics than the average mother. They are younger, less educated, more likely to be black or Hispanic, and less likely to be married.

III. Econometric Specifications

Our baseline specification for schools is

$$Y_{st} = \alpha F1_{st} + \beta F25_{st} + \gamma F50_{st} + \alpha' N1_{st} + \beta' N25_{st} + \gamma' N50_{st} + \delta X_{st} + \theta Z_{st} + d_s + e_{st}, \tag{1}$$

where Y_{st} is the fraction of students in school s in a given grade who are obese in year t; $F1_{st}$ is an indicator equal to 1 if there is a fast food restaurant within 0.1 miles of the school in year t; $F25_{st}$ is an indicator equal to 1 if there is a fast food restaurant within 0.25 miles of the school in year t; $F50_{st}$ is an indicator equal to 1 if there is a fast food restaurant within 0.5 mile of the school in year t; $N1_{st}$, $N25_{st}$, and $N50_{st}$ are similar indicators for the presence of non-fast food restaurants within 0.1, 0.25 and 0.5 miles of the school; d_s is a fixed effect for the school.

We include the controls $N1_{st}$, $N25_{st}$, and $N50_{st}$ because the presence of other restaurants in a neighborhood is likely to be a good proxy for characteristics of a neighborhood that may be correlated with the presence of a fast food restaurant and with factors that may contribute to obesity in school children, such as urbanicity and lack of space to play. Moreover, some of the hypotheses about how fast food contributes to obesity (such as through marketing to children) may be unique to fast food.

Hence, it is important to distinguish between the effects of fast food restaurants, per se, and those of other restaurants.

The vectors X_{st} and Z_{st} include school and neighborhood *time-varying* characteristics that can potentially affect obesity rates. Specifically, X_{st} is a vector of school-grade specific characteristics including fraction African-American, fraction native American, fraction Hispanic, fraction immigrant, fraction female, fraction eligible for free lunch, whether the school is qualified for Title I funding, pupil/teacher ratio, and ninth grade tests scores, as well as school-district characteristics such as fraction immigrants, fraction of non-English speaking students (limited english proficiency/english language learner), share of special education (individual educational plan) students (see Table 1A for a full list). Z_{st} is a vector of characteristics of the census block closest to the school including median income, median earnings, average household size, median rent, median housing value, racial composition, educational composition, and labor force participation. (Table 1A, again, provides the full list.) To account for heteroskedasticity caused by the fact that cells vary in size, we weight all our models by the number of students in each cell. To account for the possible correlation of the residual e_s within a school, we report standard errors clustered by school.

Other things being equal, the school fixed effects specification would be our preferred specification in the schools data. However, we also emphasize models without school fixed effects because there are many schools in our data that do not experience a change in the proximity of fast food restaurants over our sample period (and hence do not contribute to identification in the models with school fixed effects) as discussed above. Moreover, we find little evidence that the placement of fast food restaurants is related to student characteristics within the small areas that we focus on. Finally, because we focus on ninth graders, who are generally new to their high schools, the estimates without school fixed effects may closely resemble those with fixed effects since both capture the influence of new proximity to a fast food restaurant. Given that the previous literature focuses largely on cross-sectional estimates, it is of interest to compare models with and without school fixed effects in order to determine the possible magnitude of biases due to omitted variables bias. We find significant effects of close proximity to a fast food restaurant in models with and without school fixed effects.

The key identifying assumption is that after conditioning on the vector X and Z, the proximity of non-fast food restaurants and, in the panel specifications, also school fixed effects, changes in other determinants of obesity rates are not systematically correlated with changes in the proximity of fast food restaurants. In other words, in the absence of a fast food restaurant, schools that are 0.1 miles from a fast food restaurant and schools that are 0.25 miles from a fast food restaurant are assumed to have similar changes in obesity rates. This assumption is not incompatible with fast food restaurants targeting schools when opening new locations. It only requires that, *within a quarter of a mile from a school,* the exact location of a new restaurant opening is determined by idiosyncratic factors. Since the exact location of new retail establishments is determined by many factors, including the timing of when suitable locations become available, this assumption does not appear unrealistic. Below we report a number of empirical tests of this assumption.

It is important to note that the fast food restaurant indicators $F1_{st}$, $F25_{st}$, and $F50_{st}$ are not mutually exclusive. Similarly, we define the non-fast food restaurant indicators $N1_{st}$, $N25_{st}$, and $N50_{st}$ as not mutually exclusive. This means that the coefficient α, for example, is the *difference* in the effect of having a fast food restaurant within 0.1 mile and the effect of having a fast food restaurant within 0.25 miles. To compute the effect of having a fast food restaurant within 0.1 miles (relative to the case where there is no fast food restaurant within at least 0.5 miles) one needs to sum the three coefficients $\alpha + \beta + \gamma$.

When we use the sample of mothers, our econometric specification is

$$Y_{it} = \alpha F1_{it} + \beta F25_{it} + \gamma F50_{it} + \alpha' N1_{it} + \beta' N25_{it} + \gamma' N50_{\mathrm{it}} + \delta X_{it} + d_i + e_{it}, \quad (2)$$

where Y_{it} is either an indicator equal to 1 if mother i gains more than 20 kg (or 15 kg) during her t-th pregnancy or mother i's weight gain during her t-th pregnancy; X_{it} is a vector of time-varying mother characteristics including age dummies, four dummies for education, dummies for race, Hispanic status, an indicator equal to 1 if the mother smokes during pregnancy, and indicator for male child, dummies for parity, marital status, and year dummies,[12] and d_i is a mother fixed effect. To account for the possible correlation of the residual e_{it} for the same individual over time, we report standard errors clustered by mother. In an alternative set of specifications we include fixed effects for the zip code of residence of the mother rather than mother fixed effects. This specification is similar to the fixed effect specification for the schools.

Finally, there are two reasons for proximity to a fast food restaurant to change for mothers. They could stay in the same place and have a restaurant open (or close) near them. Or, they could move closer or further away from a fast food restaurant between pregnancies. In order to determine which of these two effects dominate, we also estimate models using only women who stayed in the same place between pregnancies (these women are designated stayers). In these models, the estimates reflect the estimated effects of having a restaurant open (or close) nearby between pregnancies.

One concern is the possible presence of measurement error. While our information about restaurants comes from one of the most reliable existing data sources on the location of retailers,[13] it is probably not immune to measurement error. Our empirical findings point to an effect of fast food restaurants on obesity that declines with distance. It is unlikely that measurement error alone is responsible for our empirical finding. First, measurement error is likely to induce some attenuation bias in our estimates (i.e., a downward bias). Second, even if measurement error did not induce downward bias, it would have to vary systematically with distance, and there is no obvious reason why this would be the case.[14]

[12] Also included are indicators for missing education, race, Hispanic status, smoking, and marital status.

[13] Our data on restaurant are considered by some as the "best data source for studying business location" (Jed Kolko and David Neumark 2007).

[14] As an additional check, we used Google Map to check the distance between schools and restaurants for a random sample of our schools. This comparison is complicated by three problems. First, Google Maps data are not

TABLE 2—IMPACT OF FAST FOOD ON OBESITY IN SCHOOLS: BENCHMARK RESULTS

	Percent of ninth graders that are obese			
Dependent variable	(1)	(2)	(3)	(4)
Availability of fast food restaurant within 0.1 miles	3.0807 (1.6072)*	1.7385 (0.8740)**	6.1955 (2.9446)**	6.3337 (2.8750)**
Availability of other restaurant within 0.1 miles	0.6817 (1.0308)	−0.6162 (0.5704)	1.0939 (1.9123)	1.0026 (1.8236)
Availability of fast food restaurant within 0.25 miles	−2.4859 (1.1112)**	−0.891 (0.5452)	−1.8486 (1.1812)	−1.7947 (1.2095)
Availability of other restaurant within 0.25 miles	2.1416 (0.8757)**	0.0505 (0.4895)	0.269 (1.0113)	0.0375 (0.9428)
Availability of fast food restaurant within 0.5 miles	1.3903 (0.8219)*	−0.0391 (0.4475)	−0.9173 (1.1152)	−0.8311 (1.0871)
Availability of other restaurant within 0.5 miles	1.2266 (0.8407)	0.4638 (0.4881)	0.1266 (0.9083)	−0.4151 (0.8160)
School fixed effects	—	—	X	X
Year fixed effects	—	X	—	X
School controls	—	X	—	X
Census block controls	—	X	—	X
Implied cumulative effect of exposure to fast food restaurant within 0.1 miles	1.9851 (1.5094)	0.8084 (0.8535)	3.4296 (3.0601)	3.7078 (2.9838)
R^2	0.0209	0.4296	0.636	0.6512
N	8,373	8,373	8,373	8,373

Notes: Each column is a different OLS regression. The regressions are weighted by the number of students. The dependent variable is the percentage of students in the ninth grade who are classified as obese. The mean of the dependent variable is 32.9494. The unit of observation is a school-grade-year for schools in California in 1999 and the period 2001–2007. Entries in rows 1, 3, and 5 are the coefficient on a dummy for the existence of a fast food restaurant at a given distance from the school. Entries in rows 2, 4, and 6 are coefficients on the dummy for the existence of a non-fast food restaurant at a given distance from the school. The implied cumulative effect reported in the table is the sum of the coefficients in rows 1, 3, and 5, and is the total effect of exposure to a fast food restaurant at 0.1 mile compared to no exposure to fast food restaurants within 0.5 miles. The school-level controls are from the Common Core of Data, with the addition of Star test scores for the ninth grade. The census block controls are from the closest block to the address of the school. Table 1A lists the school and census block controls. Standard errors clustered by school are in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

IV. Empirical Findings: School Sample

A. *Benchmark Estimates*

Table 2 shows our baseline empirical estimates of the effect of changes in the supply of fast food restaurants on obesity rates (see equation (1) above). The dependent

immune to measurement error. In our search, we found some instances in which Google Maps significantly misreported or missed the location of a business. Second, our data end in mid-2006, while current Google Maps reflect restaurant location at the end of 2008. There is considerable churning in this industry, so even if our data and Google data were perfectly correct, we could find some discrepancies. Third, our measure of distance is "as the crow flies," while Google Maps only provides driving distance. This latter issue is a problem because the key variable of interest for us is a dummy equal to 1 if the distance between the school and the restaurant is < 0.1 miles. Even small differences between distance measured "as the crow flies" and driving distance may lead us to incorrectly label our indicator as incorrect, when in fact it is correct. In the subsample of 30 schools that we checked by hand, we estimate a reliability ratio of 0.75. Given the three limitations described above, we consider this evidence as quite encouraging.

variable is the percentage of students in the ninth grade who are classified as obese. Each column is from a different regression. Entries are the coefficient on a dummy for the existence of a fast food restaurant at a given distance from the school (coefficients α, β, and, γ in equation (1)) and coefficients on dummies for the existence of a non-fast food restaurant at a given distance from the school (α', β', and γ' in equation 1). Recall that the fast food restaurant indicators are not mutually exclusive. Thus, the coefficient on the 0.1 miles dummy is to be interpreted as the *additional* effect of having a fast food restaurant within 0.1 mile over and above the effect of having a fast food restaurant within 0.25 miles.

In column 1 of Table 2, we report unconditional estimates. There is generally a positive association between availability of a fast food restaurant and obesity rates. Estimates in column 2 condition on school level controls, census block controls, and year effects. We note that standard errors are smaller in column 2 than in column 1, indicating that our controls do a good job absorbing other determinants of obesity, but leave enough variation for the identification of the effect of interest. With controls, the only statistically significant effect is associated with the availability of a fast food restaurant within 0.1 miles. To illustrate the interpretation of this coefficient, compare two schools that are identical, but one is located 0.09 miles from a fast food restaurant, while the other one is located 0.24 miles from a fast food restaurant. The estimate of α in column 2 indicates that in the former the obesity rate is 1.7 percentage points higher than in the latter. This estimate is both statistically significant and economically important. Compared to a mean obesity rate of 32.9, a fast food restaurant within 0.1 miles from a school results in a 5.2 percent increase in the incidence of obesity. The coefficients on availability of a fast food restaurant within 0.25 miles (β) and on availability of a fast food restaurant within 0.50 miles (γ) are statistically insignificant. Figure 1A plots these estimates together with confidence intervals. The presence of non-fast food restaurants has no effect on obesity, indicating that the effect of fast food restaurants is specific and does not generalize to any food establishment. This pattern of effects—only fast food restaurants that are very close have an effect—is consistent with a nonlinear increase in transportation costs with distance, and/or with strong psychological effects of the availability of fast food restaurants, such as temptation for consumers with self-control problems.

We can also use the estimates in Table 2 to compare the effect of having a fast food restaurant at distance of 0.1 miles, compared to not having a fast food restaurant (within 0.5 miles). The sum of coefficients $\alpha + \beta + \gamma$ (reported at the bottom of the Table 2), which captures the effect of exposure to a fast food restaurant within 0.1 miles compared to no fast food restaurant within 0.5 miles, is sizeable and positive ($0.81 = 1.7385 - 0.891 - 0.0391$), though not significant.

In columns 3 and 4 of Table 2, we present estimates with school fixed effects. By including indicators for each school, we absorb any time-invariant determinant of obesity. The estimates are identified only by schools where fast food restaurant availability varies over time. At the 0.1 mile distance, for example, there are 13 schools that add a fast food restaurant, 8 that lose a fast food restaurant, and 1 school that does both. At the 0.25 (respectively, 0.5) mile distance, 63 (respectively, 117) schools switch fast food restaurant availability in the sample. The estimates with

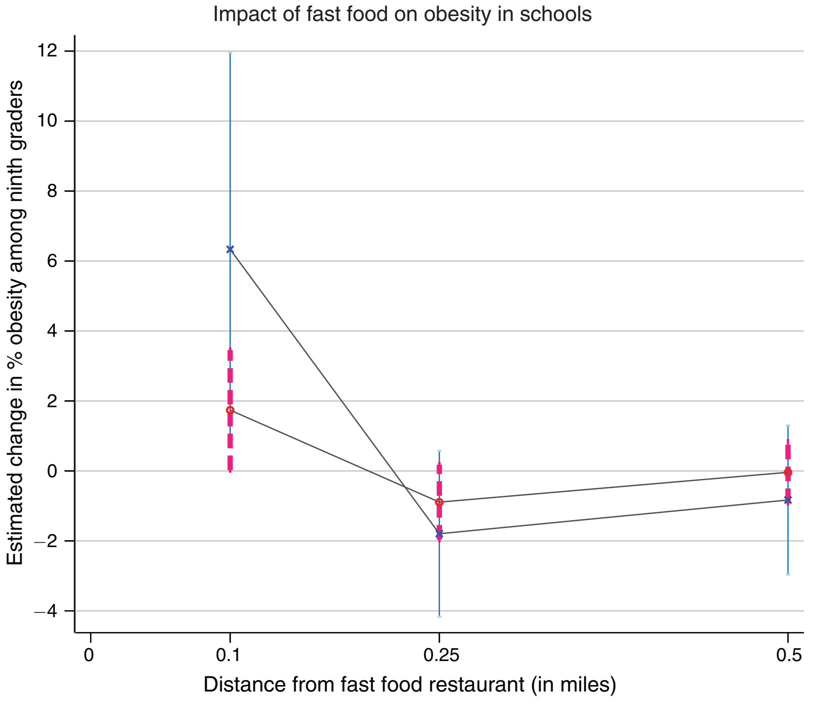

Figure 1A. Impact of Fast Food Availability on Obesity among Ninth Graders

Notes: The vertical bar represents the 95 percent confidence interval using panel estimates; the dashed vertical bar represents the 95 percent confidence interval using cross-sectional estimates.

school fixed effects point to a statistically significant effect of the availability of a fast food restaurant within 0.1 miles of 6.33 percentage points, which is larger than in the cross-sectional estimates of columns 1 and 2. This fast food restaurant effect is the same in the specification without controls (column 3) and with controls (column 4 of Table 2, and Figure 1A), indicating that once we condition on school fixed effects, there is very limited selection on the other observables. There is no evidence of a positive additional effect of the availability of a fast food restaurant within 0.25 miles or 0.5 miles. The pattern is similar to what we see in models without school fixed effects. There is no significant effect of a fast food restaurant at 0.5 or 0.25 miles, and a large positive effect at 0.1 miles.

Next, we present estimates based on an event study methodology. We examine how the past, current, and future existence of a fast food restaurant in a given location affects the current obesity rates of students at that location. Estimates are from a single regression where we include indicators for availability of fast food in years $t-3$, $t-2$, $t-1$, t, $t+1$, $t+2$, and $t+3$ for a distance of 0.1 mile, 0.25 miles, and 0.5 miles.[15] Figure 2 presents estimates of the impact of fast food availability within 0.1 miles for specifications both without and with school fixed effects. The

[15] We also include (but do not show) seven indicators for non-fast food restaurants.

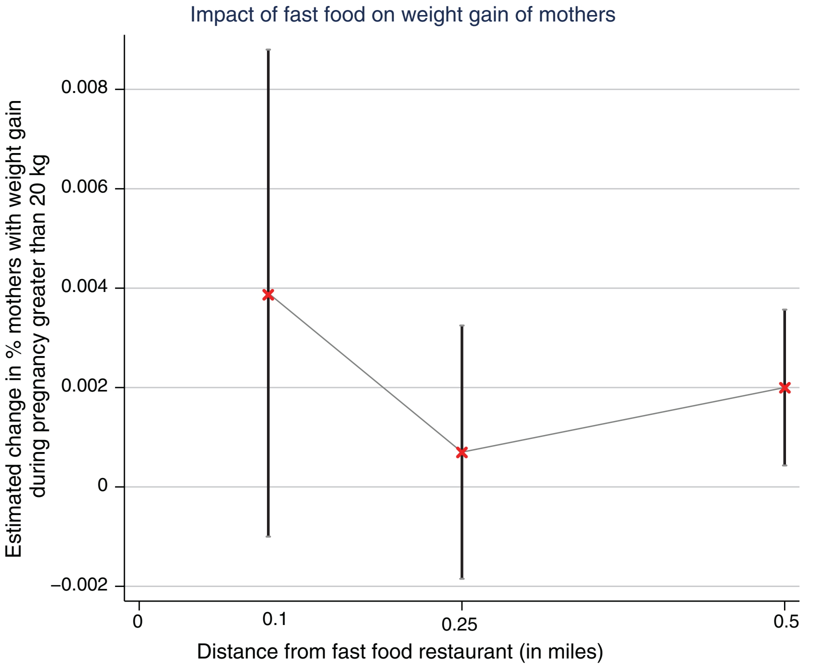

Figure 1B. Impact of Fast Food Availability on Weight Gain of Pregnant Mothers

Notes: The vertical bar represents the 95 percent confidence interval, and we use the mother fixed effects estimates. Figure 1A plots the estimated impact of exposure to fast food at 0.1, 0.25, and 0.5 miles on the obesity rate of ninth graders in the cross-section (column 2 in Table 2) and in the panel (column 4 in Table 2). Figure 1B plots the estimated impact on the probability of weight gain above 20 kg for mothers, in the specification with mother fixed effects (column 2 in Table 6). The figure plots the effect of exposure at distance j relative to the next largest distance. As such, the effect for 0.1 (respectively, 0.25) miles is the effect of exposure to fast food at 0.1 (0.25) miles, compared to exposure to fast food at 0.25 (0.5) miles. That is, it is the coefficient α (β) in equation (1). The effect for 0.5 miles captures the effect of exposure at 0.5 miles, compared to no fast food within 0.5 miles, that is, it is the coefficient γ in equation (1).

vertical bars denote 95 percent confidence intervals. If fast food restaurants open in areas that experience unobserved upward trends in the demand for fast food, it is possible that current obesity rates may be correlated with future (or lagged) fast food restaurant availability. Otherwise, we expect that future fast food restaurant exposure should not affect obesity rates. Similarly, lagged fast food restaurant presence near the school should not affect obesity rates since students in ninth grade are typically starting high school in a different location from where they attended middle school.

While the estimates are necessarily imprecise given the high degree of multicollinearity, the qualitative picture that emerges from Figure 2 is striking. Both cross-sectional estimates and panel estimates indicate that the effect of exposure occurs at time t, which is exactly the time when it is expected to occur. Estimates for the three lags and the three leads are all much closer to zero. We conclude that, conditional on current availability of a fast food restaurant, past or future availability has no discernible effect on obesity. This lends considerable credibility to our design.

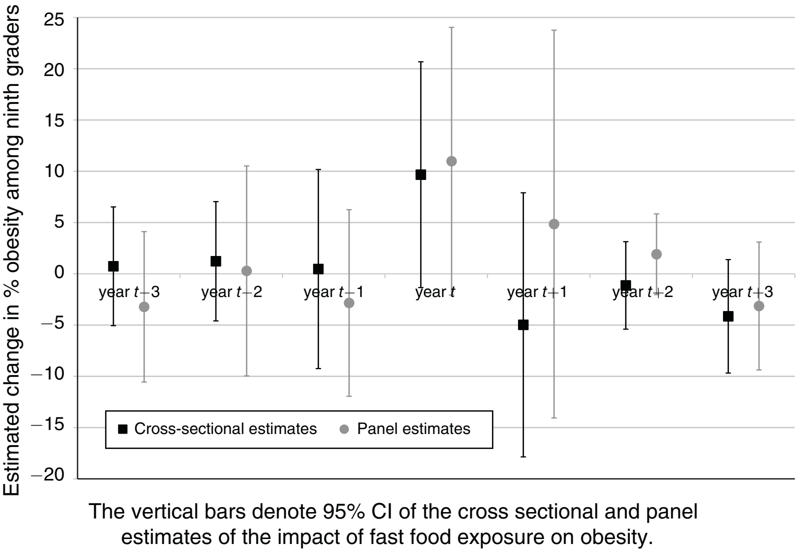

FIGURE 2. ESTIMATED IMPACT OF PAST, CURRENT, AND FUTURE EXPOSURE TO FAST FOOD ON OBESITY AMONG NINTH GRADERS

Notes: Figure 2 plots the estimated impact of exposure to fast food at 0.1 miles on the obesity rate of ninth graders in the cross-section and with school fixed effects. The estimates are from one specification including indicator variables for the presence of a fast food at distance of j miles (for $j = 0.1$, 0.25, and 0.5) in years $t-3$, $t-2$, $t-1$, t, $t+1$, $t+2$, $t+3$. As such, the estimated impact of exposure in year $t-2$, for example, should be interpreted as the impact of lagged exposure to fast food, holding constant current exposure.

B. *Magnitude of the Estimated Effect*

Are the estimated effects plausible? To investigate this question, we compute how many calories it would take per school day to move a 14-year-old boy of median height across the cut-offs for overweight status (the eighty-fifth percentile of BMI) and obesity (the ninety-fifth percentile of BMI). Based on Centers for Disease Control and Prevention (CDC) 2000 growth charts, it only takes a weight gain of 3.6 pounds to move from the eightieth to the eighty-fifth percentile of the BMI distribution. Over a period of 30 weeks,[16] this corresponds to a gain of about 80 additional calories per school day. It would take 300 additional calories to move from the nintieth to the ninety-fifth percentile of BMI, where the later is the cutoff for obesity.

Based on these calibrations, the cross-sectional estimate of a 1.7 percentage point increase in the obesity rate due to the immediate proximity of a fast food restaurant (column 2 in Table 2) corresponds to about 30 additional calories per day according to the first calculation and 100 calories per day according to the second. These amounts can be compared with the calories from a typical meal at a fast food restaurant, such as 540 calories for McDonald's Big Mac, 990 calories for Burger King's

[16] Thirty weeks is the average length of time that the ninth graders are exposed to a nearby restaurant between the beginning of high school in September and the fitness test. BMI percentiles and median height for 14-year-old boys are taken from the CDC 2000 growth charts available from www.cdc.gov/nchs/data/nhanes/growthcharts/set1/all.pdf.

Double Whopper, 570 for McDonald's regular fries, and 200 calories for a 16 ounce regular Coke.[17] Even assuming that a large portion of the calories consumed in fast food restaurants are offset by lower consumption at other meals, it is easy to obtain caloric intake increases that are consistent with the observed effects.[18]

Cara B. Ebbeling et al. (2004) report on a controlled experiment of energy intake among overweight and nonoverweight adolescents that involved offering them a fast food meal during the day and found that energy intake from the meal among all participants was extremely large (1,652 calories). What is more striking is that overweight participants consumed approximately 400 more total calories on fast food days than non-fast food days, while lean participants were able to offset their fast food intakes. Thus, there appears to be at least a subset of children who do not offset fast food calories effectively. Therefore, the estimates in Table 2 appear to be quite plausible.

C. *Additional Specifications*

In Table 3, we present estimates from a variety of alternative specifications. In column 1, we test how sensitive our results are to our definition of a fast food restaurant. Our estimates so far are based on our benchmark definition of fast food restaurants, which includes the top 10 chains (McDonald's, Subway, Burger King, Pizza Hut, Jack in the Box, Kentucky Fried Chicken, Taco Bell, Domino's Pizza, Wendy's, and Little Caesar's). As Appendix Table 1 shows, the top 10 restaurants account for 43 percent of all fast food restaurants in the four states we study. In column 1 of Table 3, we add an indicator based on a broader definition of fast food restaurants based on the Wikipedia list of fast food chains. Our broad definition starts with this list, excludes ice cream, donut, and coffee shops, and adds in all independent restaurants that have the words "pizza" or "burger" in their names. This allows us to capture some of the effect of small independent restaurants. The model indicates that this measure does not have any additional impact over and above our baseline definition of a fast food restaurant, suggesting that the top 10 fast food restaurants are qualitatively different from other fast food establishments. In column 2 of Table 3, we show estimates using another alternative measure of fast food that excludes Subway restaurants, which are arguably healthier than the other chains, from our list of top 10 fast food restaurants. The results are essentially the same as using the benchmark definition.[19]

[17] The fast food calories are from http://www.acaloriecounter.com/fast food.php. The estimate that it takes 3,500 extra calories per week to gain a pound is from the CDC and is available from http://www.cdc.gov/nccdphp/dnpa/healthyweight/index.htm

[18] The calorie intake from the typical fast food meal is an order of magnitude larger than any plausible caloric expenditure in a round trip to a fast food restaurant. It would take at most 4 minutes to stroll the distance of 1–2 blocks to a fast food restaurant that is 0.1 miles away and a 14-year-old boy of median weight (about 120 lbs) would expend about 30 calories on the trip. The weight-for-age charts for boys is available at http://www.cdc.gov/growthcharts/data/set1clinical/cj41c021.pdf, while the calorie burn rate for walking at 3.5 mph can be computed at http://www.healthdiscovery.net/links/calculators/calorie_calculator.htm.

[19] We also asked whether the availability of two or more fast food restaurants within 0.1 miles had a greater impact than the availability of one fast food restaurant within 0.1 miles, but did not find any difference. This is not surprising, given the small number of cases with two or more fast food restaurants within 0.1 miles. See the Web Appendix Table 2 for details.

Table 3—Impact of Fast Food on Obesity in Schools: Additional Models

Dependent variable	Percent of ninth graders that are obese				
	All students			Hispanic students	Black students
	(1)	(2)	(3)	(4)	(5)
Availability of fast food restaurant within 0.1 miles	1.8063 (0.9113)**			2.0067 (1.0135)**	−1.5417 (1.2056)
Availability of fast food (broad def.) restaurant within 0.1 miles	−0.4643 (0.9239)				
Availability of non-fast food restaurant within 0.1 miles	−0.707 (0.6111)				
Availability of fast food restaurant (excluding Subway) within 0.1 miles		1.7223 (0.9071)*			
Availability of other restaurant within 0.1 miles		−0.6134 (0.5648)		−0.3049 (0.6169)	−0.4451 (0.8610)
Availability of any restaurant within 0.1 miles			−0.4719 (0.5393)		
School fixed effects	—	—	—	—	—
Year fixed effects	X	X	X	X	X
School controls	X	X	X	X	X
Census block controls	X	X	X	X	X
Controls for restaurants at 0.25 and 0.5 miles	X	X	X	X	X
Average of dependent variable	32.9494	32.9494	32.9494	36.9517	35.4517
R^2	0.4299	0.4295	0.4287	0.2215	0.2516
N	8,373	8,373	8,373	6,946	2,851

Notes: Each column is a different OLS regression. The regressions are weighted by the number of students. The dependent variable in columns 1–3 is the percentage of students in the ninth grade who are classified as obese. The dependent variable in columns 4 and 5 is the percentage of Hispanic and black students, respectively, in the ninth grade who are classified as obese.The unit of observation is a school-grade-year for schools in California in 1999 and the period 2001–2007. Entries in rows 1 and 3 are the coefficient on a dummy for the existence of a fast-fast food restaurant and a non-fast food restaurant closer than 0.1 miles from the school. The entry in row 2 is the coefficient on a dummy for whether there is a fast food restaurant according to a broader definition (and not included in the benchmark definition) less than 0.1 miles from the school. The broad definition includes all restaurants classified as fast-foods by Wikipedia. The entry in row 4 is the coefficient on a dummy for proximity to one or more of the top 10 fast food chains excluding Subway.

The school-level controls are from the Common Core of Data, with the addition of Star test scores for the ninth grade. The census block controls are from the closest block to the address of the school. Table 1A lists the school and census block controls. Standard errors clustered by school in parentheses. The specifications in columns 4 and 5 include fewer observations because only school-year observations with at least 10 students in the race category report the data.

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Column 3 of Table 3 shows estimates of a model in which we do not distinguish between fast food and non-fast food restaurants. The key independent variable here is an indicator equal to one for *any* restaurant. This specification is similar to the one emphasized by Anderson and Matsa (2009). Consistent with their findings, we find no evidence that the presence of any restaurant affects obesity.

In columns 4 and 5 of Table 3, we test for racial differences. The point estimates for Hispanic students (larger in the fixed effect estimates) are similar to the ones in the whole sample. Point estimates for African Americans are smaller and not significant. This may be due to a limitation of our data which is that reporting is restricted to groups with at least ten students. Since there are relatively few African Americans in California, this restriction induces more censoring for them than for other groups. The point estimates for whites (Web Appendix Table 1) are similar to those in the whole sample. When we split the sample by gender (Web Appendix Table 1), the effect is substantially larger for female students than for male students. We also attempted to consider variation in effects by family income, using whether children were eligible for free school lunch as an income proxy. The difference in the effects for the groups with and without free lunch status is small and not statistically significant at conventional levels (not shown).

We have also considered a number of alternative specifications (Web Appendix Table 2):

- an optimal trimming model, where we include only schools that have a propensity score between 0.1 and 0.9;
- a nearest neighborhood matching specification, where we match on all the school level and block level covariates; and
- a proximity regression where we use only the subsample of schools that are within 0.25 miles of a fast food restaurant and examine the effect of being within 0.1 miles. All of these specifications yield estimates similar to those described above.[20]

D. *Threats to Identification and Placebo Analysis*

One concern with our estimates is that even after conditioning on school fixed effects and time varying student and neighborhood characteristics, the location of fast food restaurants may still be associated with other determinants of obesity that we cannot control. After all, fast food chains do not open restaurants randomly. Presumably, they open new restaurants in areas where they expect demand for fast food to be strong.

We now turn to a discussion of the plausibility of our identifying assumptions. We begin by asking whether observable characteristics of students are associated with levels of (and changes in) the availability of a fast food restaurant near a school. In Table 4, we replicate the main regressions of Table 2, but use as dependent variables six characteristics of the school, such as the fraction of the students in the school who are black (column 1); Hispanic (column 2); Asian (column 3); the share of Title 1 students (column 4); share with free lunch (column 5); and average test scores (column 6). These models exclude the school level characteristics from the regressions (i.e., the X variables), but include the census controls and the year fixed effects (the Z variables). Panel A reports estimates from models without school

[20] We also present results on the effect of fast food restaurants on alternative measures of fitness in Web Appendix Table 3 including: abdominal strength, aerobic capacity, flexibility, trunk strength, and upper body strength. Our hypothesis is that consumption of fast food should have a larger effect on obesity than on, say, strength. Models without school fixed effects point to a negative effect of fast food restaurant on flexibility. However, estimates from models with school fixed effects are generally insignificant for these measures. This finding is consistent with David M. Cutler, Edward L. Glaeser, and Jesse M. Shapiro (2003), and Sara N. Bleich et al.'s (2007) argument that rising obesity is linked to increased caloric intake and not to reduced energy expenditure.

Table 4—Impact of Fast Food on Obesity in Schools: Placebos Using Demographic Variables

Dependent variable	Share black	Share Hispanic	Share Asian	Share Title I students	Share free lunch	Average test score	Pred. obesity based on controls
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Cross-section							
Availability of fast food restaurant within 0.1 miles	−0.0039	0.0146	−0.0249	0.0653	−0.0276	−2.9162	0.9599
	(0.0101)	(0.0290)	(0.0168)	(0.0703)	(0.0295)	(2.5761)	(0.7820)
Availability of fast food restaurant within 0.25 miles	−0.0084	0.0062	0.0122	−0.0761	0.0066	1.8543	−0.6041
	(0.0074)	(0.0201)	(0.0099)	(0.0409)*	(0.0170)	(1.7399)	(0.5100)
Availability of fast food restaurant within 0.5 miles	0.0102	−0.0089	−0.0006	0.02	−0.0047	1.1212	−0.0114
	(0.0060)*	(0.0145)	(0.0072)	(0.0323)	(0.0121)	(1.2110)	(0.3743)
Panel B. School fixed-effect panel							
Availability of fast food restaurant within 0.1 miles	−0.004	−0.0017	−0.0037	−0.0365	−0.0408	0.0465	−0.0092
	(0.0042)	(0.0081)	(0.0036)	(0.0389)	(0.0280)	(1.4675)	(0.5481)
Availability of fast food restaurant within 0.25 miles	0.0027	−0.002	0.0065	0.0399	0.0023	0.557	−0.0483
	(0.0025)	(0.0064)	(0.0037)*	(0.0480)	(0.0154)	(1.2330)	(0.4146)
Availability of fast food restaurant within 0.5 miles	−0.003	−0.0022	0.0003	0.0044	0.0156	−2.4215	−0.2734
	(0.0021)	(0.0048)	(0.0026)	(0.0348)	(0.0121)	(0.8345)***	(0.1914)
School controls	—	—	—	—	—	—	—
Year fixed effects	X	X	X	X	X	X	X
Census block controls	X	X	X	X	X	X	X
Controls for availability of other restaurants	X	X	X	X	X	X	X
Average of dependent variable	0.0843	0.3804	0.1072	0.3971	0.2901	57.6665	32.8015
N	8,373	8,373	8,373	8,373	8,373	8,168	8,373

Panel C. Test of uniform distribution of fast-foods

No. fast foods at 0.25 miles—(No. fast foods at 0.1 miles* $(2.5)^2$) = −0.0135 (s.e. 0.0552), n.s.

No. fast foods at 0.5 miles—(No. fast foods at 0.1 miles* 5^2) = −0.1335 (s.e. 0.2245), n.s.

Notes: Each column is a different OLS regression. The regressions are weighted by the number of students. The dependent variables are different school-level demographic variables. The dependent variable in column 7 is the predicted share of obese students based on a regression of the share obese on all the demographic controls. The unit of observation is a school-grade-year for schools in California in the years 1999 and 2001–2007. Since the (placebo) dependent variables in these regressions are school-level demographics, the regressions do not include school controls. The census block controls are from the closest block to the address of the school and are listed in Table 1A. Standard errors clustered by school in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

fixed effects, while panel B reports estimates from school fixed effects models. Of the 36 estimated coefficients, only one is statistically significant at conventional levels, and there is no systematic pattern to the coefficients. Student characteristics do not appear to be systematically associated with the presence of fast food restaurants.

To implement a further placebo test, we generate the best linear predictor of the share of obese students using the full set of controls X and Z. Then, in column 7, we regress this variable on the variables for fast food availability, as in Table 2, including, again, only the controls Z. The regression coefficients indicate how much fast food availability loads on the same observables that predict obesity. We find that this obesity predictor is not significantly correlated with availability of fast food at any distance, either in the cross-section or in the panel specification. This indicates that selection on unobservables is not likely to be an important concern at close distances.[21]

In panel C of Table 4, we present a geographic placebo. We test for whether fast food restaurants are geographically uniformly distributed in the area around schools. If they are, we expect the number of fast food restaurants within 0.25 (respectively, 0.5) miles of a school to be 2.5^2 (respectively, 5^2) larger than the number of fast food restaurants within 0.1 mile of a school. To make the test clearer and more conservative, we do not condition on the controls that we use in the regressions. The results at the bottom of Table 4 indicate that we cannot reject the null hypothesis of uniform placement of fast food restaurants at either horizon. While the placement of fast food restaurants may still be endogenous when comparing availability at greater distances (Austin et al. 2005), at the distances that we consider in this paper, we find no evidence of endogenous placement. Overall, we find no systematic evidence of an effect of demographic controls on the proximity of fast food restaurants at very small distances from a school.[22]

E. *Effect by Grade*

This paper focuses on ninth graders, since they are newly exposed to fast food restaurants near their high schools. Students in fifth and seventh grade are also assessed in the spring using the FITNESSGRAM®, and the available fitness measures are the same as those for ninth graders. The percent of fifth and seventh graders who are obese is very similar to the share for ninth graders. However, since elementary schools tend to be smaller than high schools (with middle schools in between), there are more observations for elementary schools. Estimates for students in these grades are shown in Table 5. Compared to the estimates for ninth graders (repeated for convenience in columns 1 and 2), the estimated effect of a fast food restaurant at 0.1 miles is much smaller for seventh graders than for ninth graders. It is zero in models both with and without school fixed effects. The effect is also small for fifth graders in the models without school fixed effects, but becomes large and similar to the estimate for ninth graders in models with school fixed effects.

V. Empirical Findings: Mother Sample

We now turn to results based on weight gain during pregnancy from the Vital Statistics data. There are several motivations for this part of our analysis. While an

[21] In Web Appendix Table 4A, we present an alternative approach to documenting the extent of selection. We regress the availability of fast food at different distances on the set of demographic variables, essentially reversing the dependent and independent variables relative to Table 4. This alternative specification allows us to conduct F-tests for the significance of all the controls. The finding, as in Table 4, is that there is no evidence of selection at very close distances from a fast food restaurant.

[22] Web Appendix Table 5 presents an additional placebo similar to Figure 2. Unlike Figure 2, we include availability only in year t and in year $t + 3$ $(t - 3)$. The results are similar if we use as a placebo the availability of fast food two years ahead and two years earlier. The findings indicate that conditional on the availability of fast food restaurants in year t, availability in year $t + 3$ does not predict obesity rates. Similarly, we do not find any significant effect of the presence of a fast food restaurant within 0.1 miles of the school three years prior, even though the estimates are noisy and the contemporaneous effect is no longer significant.

Table 5—Impact of Fast Food on Obesity in Schools by Grade

Dependent variable	Percent of obese ninth graders		Percent of obese seventh graders		Percent of obese fifth graders	
	(1)	(2)	(3)	(4)	(5)	(6)
Availability of fast food restaurant within 0.1 miles	1.7385 (0.8740)**	6.3337 (2.8750)**	0.1233 (1.1135)	1.2712 (1.1135)	0.8946 (0.7124)	6.1332 (2.8280)**
Availability of other restaurant within 0.1 miles	−0.6162 (0.5704)	1.0026 (1.8236)	−0.2018 (0.4239)	−0.4833 (1.0045)	0.4267 (0.2997)	0.629 (0.6281)
Availability of fast food restaurant within 0.25 miles	−0.891 (0.5452)	−1.7947 (1.2095)	0.0777 (0.4439)	−1.5916 (1.1223)	−0.279 (0.2811)	−1.0562 (0.7568)
Availability of other restaurant within 0.25 miles	0.0505 (0.4895)	0.0375 (0.9428)	0.6333 (0.3186)**	1.2198 (0.5830)**	0.2501 (0.1918)	−0.3428 (0.4126)
Availability of fast food restaurant within 0.5 miles	−0.0391 (0.4475)	−0.8311 (1.0871)	−0.4059 (0.3157)	0.6946 (0.6353)	0.4341 (0.1844)**	0.0418 (0.4985)
Availability of other restaurant within 0.5 miles	0.4638 (0.4881)	−0.4151 (0.8160)	0.2137 (0.3748)	−1.209 (0.8322)	0.2879 (0.2312)	0.7276 (0.3905)*
School fixed effects	—	X	—	X	—	X
Year fixed effects	X	X	X	X	X	X
School controls	X	X	X	X	X	X
Census block controls	X	X	X	X	X	X
Average of dependent variable	32.9494	32.9494	32.5601	32.5601	31.7794	31.7794
R^2	0.4296	0.6512	0.465	0.6684	0.3666	0.5582
N	8,373	8,373	13,422	13,422	37,351	37,351

Notes: Each column is a different OLS regression. The regressions are weighted by the number of students. The dependent variable is the percentage of students in the specified grade who are classified as obese. The unit of observation is a school-grade-year for schools in California in the years 1999 and 2001–2007. Entries in rows 1, 3, and 5 are the coefficient on a dummy for the existence of a fast food restaurant at a given distance from the school. Entries in rows 2, 4, and 6 are coefficient on dummy for the existence of a non-fast food restaurant at a given distance from the school. The school-level controls are from the Common Core of Data, with the addition of Star test scores for the ninth grade. The census block controls are from the closest block to the address of the school. Table 1A lists the school and census block controls. Standard errors clustered by school in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

important reason for focusing on pregnant women is the availability of geographically detailed data on weight measures for a very large sample, weight gain for pregnant women is an important outcome in its own right. Excessive weight gain during pregnancy is often associated with higher rates of hypertension, C-section, and large-for-gestational age infants, as well as with a higher incidence of later maternal obesity (Erica P. Gunderson and Barbara Abrams 2000; Wanchuan Lin 2009; Brenda L. Rooney and Charles W. Schauberger 2002; Inga Thorsdottir et al. 2002; Kabiru Wanjiku and Denise Raynor 2004). Figure 3 indicates that the incidence of low APGAR scores (APGAR scores less than 8), an indicator of poor fetal health, increases significantly with weight gain above about 15–20 kg. While this relationship may not be causal, Currie and David Ludwig (2009) show that even in mother fixed effects models, high weight gain during pregnancy is associated with infants who are large for gestational age, and therefore difficult to deliver.

From the statistical point of view, the mother sample has important advantages over the school sample, since it varies at the individual level and is longitudinally linked. Since we observe weight gains for multiple pregnancies for the same mother,

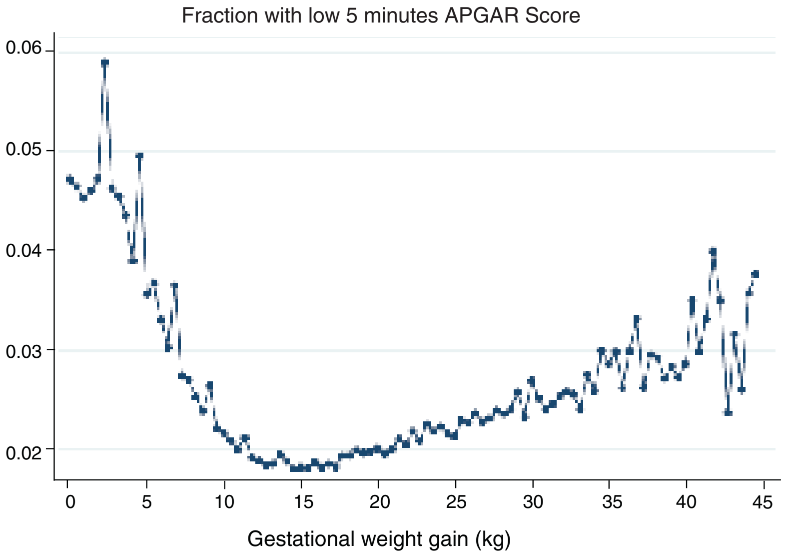

Figure 3. Correlation between Gestational Weight Gain and Low APGAR Scores

Notes: Singleton births only. Low score corresponds to APGAR5 less than 8.

Source: U.S. National Vital Statistics. Sample: 1998–2004.

we can ask how weight gain is affected by changes in the proximity to a fast food restaurant between pregnancies. These within-mother estimates control for all constant unobserved characteristics of the mother (such as whether she was exposed to a lot of fast food growing up, and her nutrition knowledge at the beginning of the period of observation).

It is important to examine the impact of exposure to fast food restaurants on adults, as well as school children. Moreover, one advantage of the weight gain measure is that unlike weight in levels, only recent exposure to fast food should matter. For these reasons, despite the lack of information on weight level and therefore obesity for mothers, the results for mothers complement the results for school children.

A. *Benchmark Estimates*

Table 6 presents our estimates of equation (2). The dependent variable in columns 1, 2, and 3 is an indicator equal to 1 if weight gain is above 20 kg. The dependent variable in column 4 is an indicator equal to 1 if weight gain is above 15 kg. We chose these measures given that the cutoff for adverse affects of pregnancy weight gain is around 15–20 kg. However, we also show estimates for continuous weight gain in column 5.

The fixed-effect models with zip-code fixed effects (column 1) and with mother fixed effects (column 2) point to a positive effect of proximity to a fast food restaurant on probability of weight gain above 20 kg. We obtain similar results for the probability of weight gain above 15 kg. (column 4), and continuous weight gain (column 5), in both cases using the specification with mother fixed effects. The

Table 6—Fast Food and Weight Gain for Mothers: Benchmark Results

Dependent variable	Weight gain during pregnancy larger than 20 kg			Weight gain > 15 kg	Weight gain (in kg)
	(1)	(2)	(3)	(4)	(5)
Availability of fast food restaurant within 0.1 miles	0.0007	0.0039	0.0054	0.0051	0.0704
	(0.0018)	(0.0025)	(0.0045)	(0.0035)	(0.0432)*
Availability of other restaurant within 0.1 miles	−0.0001	−0.0012	−0.0007	0.0003	−0.0048
	(0.0007)	(0.0010)	(0.0017)	(0.0014)	(0.0169)
Availability of fast food restaurant within 0.25 miles	0.0014	0.0007	0.0006	0.0022	0.0250
	(0.0009)	(0.0013)	(0.0022)	(0.0018)	(0.0215)
Availability of other restaurant within 0.25 miles	0.0002	0.0009	0.0006	0.0016	0.0185
	(0.0005)	(0.0008)	(0.0013)	(0.0011)	(0.0129)
Availability of fast food restaurant within 0.5 miles	0.0011	0.0020	0.0028	0.0044	0.0491
	(0.0006)*	(0.0008)**	(0.0014)**	(0.00113)***	(0.0135)***
Availability of other restaurant within 0.5 miles	0	−0.0001	−0.0033	−0.0019	−0.0165
	(0.0006)	(0.0008)	(0.0014)**	(0.0012)	(0.0136)
Sample	All mothers	All mothers	Stayers	All mothers	All mothers
Zip-code fixed effects	X	—	—	—	—
Mother fixed effects	—	X	X	X	X
Maternal characteristics	X	X	X	X	X
Implied cumulative effect of exposure to fast food restaurant within 0.1 miles	0.0031	0.0066	0.0088	0.0117	0.145
	(0.0018)*	(0.0024)***	(0.0043)**	(0.0034)***	(0.0410)***
Average of dependent variable	0.118	0.118	0.11	0.352	13.49
R^2	0.008	0.007	0.009	0.012	0.023
N	3,019,194	3,019,256	1,584,414	3,019,256	3,019,256

Notes: Each column is a different OLS regression. The unit of observation is a pregnancy for mothers with at least two births in the sample. Entries in rows 1, 3, and 5 are the coefficients on a dummy for the existence of a fast food restaurant at a given distance from the mother's residence. Entries in rows 2, 4, and 6 are coefficients on dummy for the existence of a non-fast food restaurant at a given distance from the mother's residence. The sample in column 3 is restricted to mothers who stay at the same place between pregnancies. The implied cumulative effect reported in the table is the sum of the coefficients in rows 1, 3, and 5, and is the total effect of exposure to a fast food restaurant at 0.1 mile compared to no exposure to fast food restaurants within 0.5 miles. All the regressions include a full set of demographic controls listed in Table 1B. Age was controlled for using single year of age dummies. Regressions also included indicators for missing maternal education, race, ethnicity, smoking, child gender, parity, and maternal marital status, and dummies for each year of birth. Standard errors clustered by zip code in column 1 and by mother (columns 2–5) in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

availability of a fast food restaurant within 0.5 miles is associated with an increase of 0.19 percentage points (1.6 percent) in the probability of weight gain larger than 20 kg, an increase of 0.44 percentage points (1.3 percent) in the probability of weight gain larger than 15 kg, and an increase of 0.049 kg (0.04 percent) in weight gain. As in the school sample, we find no evidence that non-fast food restaurants are associated with positive effects on weight gain.

Figure 1B shows the estimates of exposure to fast food at various distances for the benchmark models (column 2). Compared to the effect of exposure at 0.5 miles, there is a monotonic increase in the effect of availability from 0.5 miles, to 0.25 miles, and 0.1 miles, though the difference from the effect at 0.5 miles is not statistically significant. For ninth graders, instead, only availability of a fast food restaurant within 0.1 miles seems to matter, and fast food restaurants further away have no discernible impact on obesity.

In these mother fixed effects models, proximity to a restaurant may change either because a restaurant opens or closes, or because the mother changes location. In order to isolate the effect of the former, we restrict the sample to mothers who did not move between births. Results for this subsample (column 3) on the effect of proximity to a fast food restaurant are somewhat larger than for the full sample (column 2).

B. *Magnitude of the Estimated Effect*

The estimated effect of exposure to fast food restaurants at a 0.5 mile distance is to increase the weight gain of mothers during pregnancy by 49 grams (Table 6, column 5). Dividing this weight gain of about 0.1 pounds by the approximately 270 days of pregnancy yields an increase in caloric intake due to fast food of about 1.3 calories per day. (This calculation uses the CDC estimate that 3,500 additional calories induces a 1-pound weight increase.) Even the larger estimate of weight gain for proximity to a fast food restaurant at 0.1 mile corresponds to only an additional 4 calories per day. It is the large size of the dataset that provides us with the precision needed to identify such small effects. Overall, the caloric impacts of proximity to a fast food restaurant for mothers are one to two orders of magnitude smaller than the estimates for children. The findings are consistent with higher transport costs for the ninth graders (who cannot drive) relative to mothers.

C. *Additional Specifications*

Table 7 shows estimates from a number of additional specifications. This Table follows the structure of Table 3. Columns 1-3 present models in which only one measure of restaurant availability is included in each regression, namely availability within 0.5 miles.

In column 1, we test whether a broader definition of a fast food restaurant generates different results. As we did for schools, the broader definition is based on the Wikipedia list, excludes ice cream, donut, and coffee shops, and adds in all independent restaurants that have the words "pizza" or "burger" in their names. The model includes the indicator for one of the top 10 fast food restaurants within 0.5 miles, an indicator for the presence of another fast food restaurant within 0.5 miles, and an indicator for the presence of a non-fast food restaurant in this radius. The broader definition does not have any additional impact over and above the baseline "top 10" definition, suggesting that there is something unique about the largest and most widely known fast food restaurant brands.[23] Column 2 shows estimates from a model which excludes Subway from the top 10, since Subway is arguably healthier than the other chains; the estimates are very similar to the baseline

[23] Robinson et al. (2007) report that young children consistently prefer food wrapped in familiar fast food packaging, suggesting that the advertising conducted by large chains is effective in spurring demand.

Table 7— Impact of Fast Food on Weight Gain Larger than 20kg: Additional Models

Dependent variable	Weight gain during pregnancy larger than 20 kg						
Sample	All mothers			Hispanic mothers	Black mothers	High school or less	Some college or more
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Availability of fast food restaurant within 0.5 miles	0.0019 (0.0009)*			0.0022 (0.0013)*	0.0066 (0.0016)***	0.0033 (0.0009)***	0.0002 (0.0012)
Availability of fast food (broad def.) restaurant within 0.5 miles	0.0009 (0.0009)						
Availability of non-fast food restaurant within 0.5 miles	−0.0002 (0.0008)			−0.0015 (0.0015)	−0.0032 (0.0021)	0.0000 (0.0010)	0.0004 (0.0011)
Availability of fast food restaurant within 0.5 miles excluding Subway		0.0025 (0.0007)***					
Availability of other restaurant within 0.5 miles		0.0002 (0.0008)					
Availability of any restaurant within 0.5 miles			0.0011 (0.0007)				
Zip-code fixed effects	—	—	—	—	—	—	—
Mother fixed effects	X	X	X	X	X	X	X
Maternal characteristics	X	X	X	X	X	X	X
Average of dependent variable	0.126	0.126	0.126	0.101	0.131	0.126	0.106
R^2	0.006	0.007	0.007	0.011	0.002	0.007	0.007
N	3,019,256	3,019,256	3,019,256	794,535	495,045	1,779,895	1,236,989

Notes: Each column is a different OLS regression. The unit of observation is a pregnancy for mothers with at least two births in the sample. Entries in rows 1 and 3 are the coefficients on a dummy for the existence of a fast fast food restaurant and a non-fast food restaurant within 0.5 miles from the mother's residence. The entry in row 2 is the coefficient on a dummy for whether there is a fast food restaurant according to a broader definition (and not included in the benchmark definition) within 0.5 miles from the mother's residence. The entry in row 4 is the coefficient on a dummy for the existence of a fast food restaurant from one of the top 10 fast food chains excluding Subway. All the regressions include a full set of demographic controls listed in Table 1B. Age was controlled for using single year of age dummies. Regressions also included indicators for missing maternal education, race, ethnicity, smoking, child gender, parity, and maternal marital status, and dummies for each year of birth. Standard errors clustered by mother in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

estimates. Column 3 reports estimates of a model where the independent variable is an indicator equal to 1 for *any* restaurant. Similar to our findings for schools and consistent with Anderson and Matsa (2009), we find no evidence that the presence of any restaurant affects weight gain during pregnancy.

In columns 4-7 we investigate whether weight gain varies by ethnicity and maternal education. The effect of a new fast food restaurant is largest for African American mothers followed by Hispanic mothers, with no effect for non-Hispanic white mothers. In particular, the coefficient for African American mothers, 0.0066, is three times the coefficient for the average mother. Relative to the average of the dependent variable for African Americans, this amounts to a 5 percent increase in the probability of weight gain over 20 kg, a large effect. When we consider differences on the basis of education, we find that the impact is much larger in the less educated group, and that, indeed, there is no effect on more educated mothers. The effect of non-fast food restaurants is reliably zero across the different racial and educational categories.

As in the school sample, we have also considered a number of alternative specifications (Web Appendix Table 6):

- an optimal trimming model where we include only mothers that have a propensity score between 0.1 and 0.9 or being within 0.5 miles of a fast food restaurant;
- a proximity regression where we use only the subsample of mothers that are within 1 mile of a fast food restaurant and examine the effect of being within 0.5 miles; and
- a mother fixed effect model where we allow for a larger effect of proximity to two or more fast food restaurants. These specifications yield estimates similar to those described above, with no additional effect of a second fast food.

We have also estimated the effects of fast food restaurants on some additional birth outcomes (Web Appendix Table 7). The results suggest that the availability of a top 10 fast food restaurant within 0.5 miles of the mother's residence is associated with a slightly higher incidence of maternal diabetes. There is no effect on the probability that the mother had a very low weight gain (clinically defined as less than 7.26 kg) or on the probability of low birth weight.

D. *Threats to Identification and Placebo Analysis*

In column 1 of Table 8, we ask whether there is evidence of changes in pregnancy weight gain as a function of *future* fast food restaurant openings. While *current* fast food restaurants within 0.50 miles increase the current probability of weight gain above 20 kg, there is no evidence that *future* fast food restaurants increase weight gain. This is consistent with our identifying assumption. Column 2 shows estimates from models that include indicators for whether there was a fast food restaurant in the mother's current location three years ago. This test is not as strong as the other because it is possible that lagged exposure to a fast food restaurant could have an effect on current weight gain. Here both current proximity to a fast food restaurant and lagged proximity to a fast food restaurant have positive coefficients in the regression for weight gain over 20 kg, but neither coefficient is statistically significant.[24]

In columns 3 and 4, we undertake a placebo test of a different type, asking whether the availability of fast food restaurants is correlated with individual-level demographics, conditional on mother fixed effects. The few variables that are time-varying within mothers include smoking during pregnancy and marital status. If

[24] We obtained very similar results if we examined one year or two year leads and lags.

Table 8—Impact of Fast Food on Weight Gain: Placebos

Dependent variable	Weight gain during pregnancy > 20 kg: Placebos based on leads (1)	Weight gain during pregnancy > 20 kg: Placebos based on lags (2)	Mother smokes: Placebos based on demographic variables (3)	Mother is married: Placebos based on demographic variables (4)
Availability of fast food restaurant within 0.1 miles			0.0001 (0.0019)	0.0007 (0.0028)
Availability of other restaurant within 0.1 miles			0.0012 (0.0007)	−0.0016 (0.0011)
Availability of fast food restaurant within 0.25 miles			0.0002 (0.0009)	−0.0002 (0.0014)
Availability of other restaurant within 0.25 miles			0.0001 (0.0006)	−0.0008 (0.0008)
Availability of fast food restaurant within 0.5 miles	0.0035 (0.0011)***	0.0010 (0.0012)	0.0007 (0.0006)	0.0002 (0.0009)
Availability of other restaurant within 0.5 miles	−0.0006 (0.0011)	−0.0021 (0.0012)*	0.0021 (0.0006)***	−0.0001 (0.0009)
Availability of fast food restaurant within 0.5 miles 3 years later	−0.0014 (0.0011)			
Availability of other restaurant within 0.5 miles 3 years later	0.0012 (0.0012)			
Availability of fast food restaurant within 0.5 miles 3 years earlier		0.0019 (0.0013)		
Availability of other restaurant within 0.5 miles 3 years earlier		0.0025 (0.0012)**		
Zip-code fixed effects	—	—	—	—
Mother fixed effects	X	X	X	X
Maternal characteristics	X	X	X	X
R^2	0.007	0.008	0.008	0.047
N	3,019,256	2,694,834	3,005,825	2,889,618

Notes: Each column is a different OLS regression. The unit of observation is a pregnancy for mothers with at least two births in the sample. Entries in rows 1, 3, and 5 are coefficients on dummies for the existence of a fast food restaurant and the entries in rows 2, 4, and 6 are coefficients on dummies for the existence of a non-fast food restaurant, respectively, within the specified distances from the mother's residence. Entries in rows 7 and 8 are coefficients on a dummy for the existence of a fast food restaurant and a non-fast food restaurant respectively within 0.5 miles from the mother's residence three years after the pregnancy. Entries in rows 9 and 10 are coefficients on a dummy for the existence of a fast food restaurant and a non-fast food restaurant, respectively, within 0.5 miles from the mother's residence three years before the pregnancy. All the regressions include a full set of demographic controls listed in Table 1B. Age was controlled for using single year of age dummies. Regressions also included indicators for missing maternal education, race, ethnicity, smoking, child gender, parity, and maternal marital status, and dummies for each year of birth. Standard errors clustered by mother in parentheses.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

our identifying assumption is correct, these two outcome variables should not be correlated with availability of fast food restaurants. Indeed, we find no evidence that probability of smoking or marriage rates are correlated with fast food restaurants at any distance, although the probability of smoking appears to be correlated with availability of non-fast food restaurants. In Table 3B, we present further evidence on predictors of the availability of fast food restaurants.

VI. Conclusions

This paper investigates the health consequences of proximity to fast food restaurants for two vulnerable groups: young teens and pregnant women. Our results point to a significant effect of proximity to fast food restaurant on the risk of obesity, though the magnitude of the effect is very different for school children and adults. The presence of a fast food restaurant within one-tenth of a mile of a school is associated with at least a 5.2 percent increase in the obesity rate in that school (relative to the presence at 0.25 miles). Consistent with highly nonlinear transportation costs for school children, we find no evidence of an effect at 0.25 miles and at 0.5 miles. The effect at 0.1 miles distance is equivalent to an increase in daily caloric consumption of 30 to 100 calories due to proximity of fast food. The effect for pregnant women is quantitatively smaller and more linear in distance. A fast food restaurant within half a mile of a residence results in a 1.6 percent increase in the probability of gaining over 20 kg. This effect increases to a 5.5 percent increase when a fast food restaurant is within 0.1 miles from the residence of the mother. The effect at 0.5 miles translates into a daily caloric intake of 1 to 4 calories, two orders of magnitudes smaller than for school children, though for African American mothers, the effects are three times larger.

The quantitative difference in the impact of fast food between school children and mothers, and between mothers of different races has potential policy implications. To the extent that the estimates for mothers are representative of the estimates for adults with good transportation options, attempts to limit the presence of fast food in residential areas are unlikely to have a sizeable impact on obesity. Instead, narrower policies aimed at limiting access to fast food could have a sizable impact on populations with limited ability to travel, such as school children, or women in inner city neighborhoods.

Using our estimates, we can do a calibration of the impact of fast food restaurant penetration on school children and women. Taking into account that only about 6.7 percent of schools in our sample have a fast food restaurant within 0.1 miles, fast food restaurants near schools can be responsible for only 0.5 percent of the increase in obesity over the last 30 years among ninth graders.[25] Still, the results suggest that measures designed to limit access to fast food among teenagers more broadly (such as restrictions on advertising to children, or requirements to post calorie counts) could have a beneficial effect.[26]

If we assume that the effect of fast food on weight gain for pregnant mothers is the same as for nonpregnant women (an admittedly strong assumption that is likely to give an upper bound estimate), then fast food restaurants near a woman's

[25] According to our measure, about 33 percent of ninth graders in California were obese during the 1999–2007 period. Since obesity among adolescents (age 12–19) approximately tripled from 1970 to the late 1990s, we estimate the increase in obesity of ninth graders in the past 30 years to be about 22 percentage points. Hence, we compute the effect as 1.7 percentage points (the estimated impact of fast food on obesity at 0.1 miles) multiplied by 0.067 (the share of schools at 0.1 miles in 1999–2007, assumed to be zero in the 1960s) divided by 22 percentage points.

[26] Bryan Bollinger, Phillip Leslie, and Alan Sorensen (2009) find that posting calorie counts in Starbucks in New York City reduced calories consumed by about 6 percent, which is significant, but not large enough to have a major impact on obesity rates by itself.

residence could be responsible for about 2.7 percent of the increase in weight in the last 10 years among women.[27] While we cannot explain a large share of the changes in obesity and weight in either case, a potential explanation of the possibly larger fraction explained for mothers is that the effect is found at a longer distance (0.5 miles). The second is the longer assumed exposure time. If, for example, having a fast food restaurant near the school continued to influence children's eating habits throughout high school, then the cumulative effect for teens might well be larger than that estimated here.

These findings contribute to the debate about the impact of fast food on obesity by providing credible evidence on magnitudes of the effect of fast food. Still, this research leaves several questions unanswered. We cannot speculate about the generalizability of our research to other samples. It is possible that adolescents and pregnant women are uniquely vulnerable to the temptations of fast food restaurants. In addition, our research cannot distinguish between a rational price-based explanation of the findings and a behavioral self-control-based explanation. Finally, since fast food is ubiquitous in United States, we cannot study the impact of a fast food restaurant entry in a society where fast food is scarce. We hope that some of these questions will be the focus of future research.

Appendix 1
Definition of Fast food restaurant

There is little consensus about the definition of fast food in the literature. For example, the American Heritage Dictionary definies fast food as "inexpensive food, such as hamburgers and fried chicken, prepared and served quickly." While everyone agrees that prominent chains such as McDonald's serve fast food, there is less agreement about whether smaller, independent restaurants are also "fast food."

The Census of Retail Trade defines a fast food establishment as one that does not offer table service. Legislation recently passed in Los Angeles imposing a moratorium on new fast food restaurants in south central Los Angeles defined fast food establishments as those that have a limited menu, items prepared in advance or heated quickly, no table service, and disposable wrappings or containers (Abdollah 2007). However, these definitions do not get at one aspect of concern about fast food restaurants, which is their heavy reliance on advertising, and easy brand recognition.

We constructed several different measures of fast food. Our benchmark definition of fast food restaurants focuses on the top 10 chains, which are McDonald's, Subway, Burger King, Pizza Hut, Jack in the Box, Kentucky Fried Chicken, Taco Bell, Domino's Pizza, Wendy's, and Little Caesar's. We have also constructed a broader definition using Wikipedia's list of national fast food chains (en.wikipedia.

[27] CDC (using NHANES data) reports that obesity has risen by about 10 percentage points for 20–34-year-old females over the past 10 years (from 18.5 percent in the 1988–94 wave to 28.4 percent in the 1999–2002 wave) and that the average weight in this group has increased by about 6.7 kilograms. Our estimates indicate that a fast food restaurant within 0.5 miles of a residence increases weight gain by 49 grams over 9 months, which over a 10-year period translates to 650 grams. Since fast food restaurants are within 0.5 miles of a residence (in our data) for 27.7 percent of women, fast food restaurant proximity can have contributed to 650 grams times 0.277 divided by 6,700 grams, which equals 2.7 percent.

Table A1—Fast Food Restaurants and Other Restaurants

Top 10 fast food restaurants			Major fast food restaurants in Wikipedia list and not in top 10 list			Major restaurants in non-fast food category		
Rank (1)	Name (2)	Percent (3)	Rank (4)	Name (5)	Percent (6)	Rank (7)	Name (8)	Percent (9)
1	McDonalds	8	1	Starbucks	12	1	IHOP	0.002
2	Subway	7	2	Dairy Queen	7	2	Sizzler	0.002
3	Burger King	5	3	Baskin Robbins	6	3	Togo's Eatery	0.001
4	Taco Bell	4	4	Jamba Juice	5	4	Chili's	0.001
5	Pizza Hut	4	5	Fosters Freeze	5	5	Applebee's	0.001
6	Little Caesars	3	6	Orange Julius	4	6	TCBY	0.001
7	KFC	3	7	Smoothie King	4	7	Cocos	0.001
8	Wendy's	3	8	Juice Stop	4	8	Aramark	0.001
9	Domino's Pizza	3	9	Braum's	3	9	Big Boy	0.001
10	Jack in the Box	3	10	Moe's Southwest	2	10	Outback	0.001

Notes: Data on restaurant establishments are from Dun & Bradstreet. "Percent" in column 3 is the number of establishments of the relevant chain over the total number of fast food restaurants. "Percent" in column 6 is the number of establishments of the relevant chain over the total number of restaurants in the Wikipedia list excluding the top 10 chains. "Percent" in column 9 is the number of establishments of the relevant chain over the total number of restaurants, excluding fast food restaurants and restaurants on the Wikipedia list. See discussion in Appendix 1 for more details on our classification of restaurants.

org/wiki/Fast_food). Wikipedia considers fast food to be "food cooked in bulk and in advance and kept warm, or reheated to order." Our broadest definition starts with this list, excludes ice cream, donut, and coffee shops, and adds in all independent restaurants from our Dun and Bradstreet list that have the words "pizza" or "burger" in their names. The definition of "other restaurant" depends on the definition of fast food.

As discussed in the paper, we find a larger impact of the top 10 fast food chains than for the broader definition of fast foods. To conserve space, we show estimates for the broad definition excluding ice cream, donuts, and coffee shops, and for the top 10 chains.

Appendix Table 1 shows more information about the top 10 fast food restaurants, other major restaurant chains, and chains that are not counted as fast food for the four states in our study (California, Michigan, New Jersey, and Texas).

REFERENCES

Anderson, Michael, and David A. Matsa. 2009. "Are Restaurants Really Supersizing America?" Unpublished.

Anderson, Patricia M., and Kristin F. Butcher. 2005. "Reading, Writing and Raisinets: Are School Finances Contributing to Children's Obesity?" National Bureau of Economic Research Working Paper 11177.

Anderson, Patricia M., Kristin F. Butcher, and Phillip B. Levine. 2003. "Maternal Employment and Overweight Children." *Journal of Health Economics*, 22(3): 477–504.

Austin, S. Bryn, Steven J. Melly, Brisa N. Sanchez., Aarti Patel, Stephen Buka, and Steven L. Gortmaker. 2005. "Clustering of Fast-Food Restaurants Around Schools: A Novel Application of Spatial Statistics to the Study of Food Environments." *American Journal of Public Health*, 95(9): 1575–81.

Bleich, Sara N., David Cutler, Christopher Murray, and Alyce Adams. 2008. "Why is the Developed World Obese?" *Annual Review of Public Health*, 29: 273–95.

Bollinger, Bryan, Phillip Leslie, and Alan Sorensen. 2009. "Calorie Posting in Chain Restaurants." Unpublished.

Burkhauser, Richard V., and John Cawley. 2008. "Beyond BMI: The Value of More Accurate Measures of Fatness and Obesity in Social Science Research." *Journal of Health Economics*, 27(2): 519–29.

Cawley, John, and Feng Liu. 2007. "Maternal Employment and Childhood Obesity: A Search for Mechanisms in Time Use Data." National Bureau of Economic Research Working Paper 13600.

Chou, Shin-Yi, Michael Grossman, and Henry Saffer. 2004. "An Economic Analysis of Adult Obesity: Results from the Behavioral Risk Factor Surveillance System." *Journal of Health Economics*, 23(3): 565–87.

Chou, Shin-Yi, Inas Rashad, and Michael Grossman. 2008. "Fast-Food Restaurant Advertising on Television and Its Influence on Childhood Obesity." *Journal of Law and Economics*, 51(4): 599–618.

Courtemanche, Charles, and Art Carden. 2008. "The Skinny on Big-Box Retailing: Wal-Mart, Warehouse Clubs, and Obesity." www.unc.edu/the/archives/courtemanche.pdf.

Currie, Janet, and David Ludwig. 2009. "The Relationship Between Pregnancy Weight Gain and Birth Weight: A Within Family Comparison." Unpublished.

Cutler, David M., Edward L. Glaeser, and Jesse M. Shapiro. 2003. "Why Have Americans Become More Obese?" *Journal of Economic Perspectives*, 17(3): 93–118.

Davis, Brennan, and Christopher Carpenter. 2009. "Proximity of Fast-Food Restaurants to Schools and Adolescent Obesity." *American Journal of Public Health*, 99(3): 505–10.

DellaVigna, Stefano. 2009. "Psychology and Economics: Evidence from the Field." *Journal of Economic Literature*, 47(2): 315–72.

Dunn, Richard A. 2008. "Obesity and the Availability of Fast-Food: An Instrumental Variables Approach." Unpublished.

Ebbeling, Cara, B., Kelly B. Sinclair, Mark A. Pereira, Erica Garcia-Lago, Henry A. Feldman, and David S. Ludwig. 2004. "Compensation for Energy Intake from Fast Food Among Overweight and Lean Adolescents." *Journal of the American Medical Association*, 291(23): 2828–33.

Gunderson, Erica P., and Barbara Abrams. 2000. "Epidemiology of Gestational Weight Gain and Body Weight Changes after Pregnancy." *Epidemiologic Reviews*, 22(2): 261–74.

Kolko, Jed, and David Neumark. 2007. *Business Location Decisions and Employment Dynamics in California*. Public Policy Institute of California Report. San Francisco, November. http://www.ppic.org/content/pubs/report/R_1107JKR.pdf.

Lakdawalla, Darius, and Tomas Philipson. 2002. "The Growth of Obesity and Technological Change: A Theoretical and Empirical Examination." National Bureau of Economic Research Working Paper 8946.

Laibson, David. 2001. "A Cue-Theory of Consumption." *Quarterly Journal of Economics*, 116(1): 81–119.

Lin, Wanchuan. 2009. "Why Has the Health Inequality among Infants in the US Declined? Accounting for the Shrinking Gap." *Health Economics*, 18(7): 823–41.

Mair, Julie Samia, Matthew W. Pierce, and Stephen P. Teret. 2005. "The Use of Zoning to Restrict Fast Food Outlets: A Potential Strategy to Combat Obesity." http://www.publichealthlaw.net/Zoning%20Fast%20Food%20Outlets.pdf.

Philipson, Tomas, and Richard Posner. "Economics of Obesity: A Decade of Research." Unpublished.

Rashad, Inas, Michael Grossman, and Shin-Yi Chou. 2006. "The Super Size of America: An Economic Estimation of Body Mass Index and Obesity in Adults." *Eastern Economic Journal*, 32(1): 133–48.

Robinson, Thomas N., Dina L. G. Borzekowski, Donna M. Matheson, and Helena C. Kraemer. 2007. "Effects of Fast Food Branding on Young Children's Taste Preferences." *Archives of Pediatric and Adolescent Medicine*, 161(8): 792–97.

Rooney, Brenda L., and Charles W. Schauberger. 2002. "Excess Pregnancy Weight Gain and Long-Term Obesity: One Decade Later." *Obstetrics and Gynecology*, 100(2): 245–52.

Rosenheck, R. 2008 "Fast Food Consumption and Increased Caloric Intake: A Systematic Review of a Trajectory Towards Weight Gain and Obesity Risk." *Obesity Reviews*, 9(6): 535–47.

Thomadsen, Raphael. 2001. "Price Competition in Industries with Geographic Differentiation: Measuring the Effect of Location on Price in the Fast Food Industry." Unpublished.

Thorsdottir, Inga, Johanna E. Torfadottir, Bryndis E. Birgisdottir, and Reynir T. Geirsson. 2002. "Weight Gain in Women of Normal Weight before Pregnancy: Complications in Pregnancy or Delivery and Birth Outcome." *Obstetrics and Gynecology*, 99(5): 799–806.

Wanjiku, Kabiru, and B. Denise Raynor. 2004. "Obstetric Outcomes Associated with Increase in BMI Category During Pregnancy." *American Journal of Obstetrics and Gynecology*, 191(3): 928–32.

This article has been cited by:

1. Patricia I. Ritter. 2023. Soda expansion in the tropics: The effect on obesity rates among women without piped water at home. *Economics & Human Biology* **51**, 101274. [Crossref]
2. Faqin Lin, Rui Wang, Yutong Lv, Feng Kuo. 2023. Weight gains from multinational fast-food restaurants: Evidence from China. *Agribusiness* **367**. . [Crossref]
3. Sangeeta Bansal, Yanhong Jin. 2023. Heterogeneous Effects of Obesity on Life Expectancy: A Global Perspective. *Annual Review of Resource Economics* **15**:1, 433-554. [Crossref]
4. Lingxiao Wang, Yuqing Zheng, Harry M. Kaiser. 2023. Do taxes on groceries increase body weight and restaurant food expenditures? Theory and evidence from the PSID data. *Food Policy* **118**, 102476. [Crossref]
5. Adam T. Peterson, Veronica J. Berrocal, Emma V. Sanchez-Vaznaugh, Brisa N. Sánchez. 2023. How close and how much? Linking health outcomes to built environment spatial distributions. *The Annals of Applied Statistics* **17**:2. . [Crossref]
6. Samia Badji, Nicole Black, David W. Johnston. 2023. Economic, Health and Behavioural Consequences of Greater Gambling Availability. *Economic Modelling* **123**, 106285. [Crossref]
7. Marit Hinnosaar. 2023. The Persistence of Healthy Behaviors in Food Purchasing. *Marketing Science* **42**:3, 521-537. [Crossref]
8. María J. Prados, Nancy Nicosia, Ashlesha Datar. 2023. Impact of built, social, and economic environments on adolescent obesity and related health behaviors. *Obesity* **31**:4, 1085-1094. [Crossref]
9. Ashlesha Datar, Nancy Nicosia, Anya Samek. 2023. Heterogeneity in place effects on health: The case of time preferences and adolescent obesity. *Economics & Human Biology* **49**, 101218. [Crossref]
10. Shi Purun, Zhengxiu Sun, Jiaying Cao, Zhile Li. 2023. Has new rural pension system reduced the intake of junk food among rural older adults? Evidence from China. *Frontiers in Public Health* **11**. . [Crossref]
11. Brennan Davis, Cornelia Pechmann. 2023. When Students Patronize Fast-Food Restaurants near School: The Effects of Identification with the Student Community, Social Activity Spaces and Social Liability Interventions. *International Journal of Environmental Research and Public Health* **20**:5, 4511. [Crossref]
12. Jun Jiang, Patrick W. C. Lau, Yanhui Li, Di Gao, Li Chen, Manman Chen, Ying Ma, Tao Ma, Qi Ma, Yi Zhang, Jieyu Liu, Xingxing Wang, Yanhui Dong, Yi Song, Jun Ma. 2023. Association of fast-food restaurants with overweight and obesity in school-aged children and adolescents: A systematic review and meta-analysis. *Obesity Reviews* **24**:3. . [Crossref]
13. Luna Dolezal, Tanisha Spratt. 2023. Fat shaming under neoliberalism and COVID-19: Examining the UK's Tackling Obesity campaign. *Sociology of Health & Illness* **45**:1, 3-18. [Crossref]
14. Kerstin Ostermann, Johann Eppelsheimer, Nina Gläser, Peter Haller, Martina Oertel. 2022. Geodata in labor market research: trends, potentials and perspectives. *Journal for Labour Market Research* **56**:1. . [Crossref]
15. Yoosun Park, James W. Quinn, Philip M. Hurvitz, Jana A. Hirsch, Jeff Goldsmith, Kathryn M. Neckerman, Gina S. Lovasi, Andrew G. Rundle. 2022. Addressing patient's unmet social needs: disparities in access to social services in the United States from 1990 to 2014, a national times series study. *BMC Health Services Research* **22**:1. . [Crossref]

16. Katharina Wabnitz, Carmen Klinger, Peter von Philipsborn. 2022. Diabetogene Umweltfaktoren. *Die Diabetologie* **18**:7, 833-843. [Crossref]
17. Rebecca L. C. Taylor. 2022. It's in the bag? The effect of plastic carryout bag bans on where and what people purchase to eat. *American Journal of Agricultural Economics* **104**:5, 1563-1584. [Crossref]
18. Peter Congdon, Dickson Amugsi. 2022. Editorial: The obesity epidemic: Causes, context, prevention. *Frontiers in Public Health* **10**. . [Crossref]
19. Chia-Wen Wang, Duan-Rung Chen, Chang-Chuan Chan, Yen-Po Yeh, Hsiu-Hsi Chen. 2022. 'I Knew I Should Stop, but I Couldn't Control Myself': a qualitative study to explore the factors influencing adolescents' consumption of sugar-sweetened beverages and sugary snacks from a socio-ecological perspective. *Public Health Nutrition* **25**:9, 2465-2474. [Crossref]
20. Lipeng Chen, Wanlin Liu. 2022. The effect of Internet access on body weight: Evidence from China. *Journal of Health Economics* **85**, 102670. [Crossref]
21. Eser SÖZEN, Timuçin BARDAK, Selahattin BARDAK. 2022. FP-Growth Algoritması Kullanılarak Tüketiciler ve Mobilya Kullanım Süresi Arasındaki İlişkilerin Belirlenmesi. *Bartın Orman Fakültesi Dergisi* **24**:2, 194-201. [Crossref]
22. Jan Marcus, Thomas Siedler, Nicolas R. Ziebarth. 2022. The Long-Run Effects of Sports Club Vouchers for Primary School Children. *American Economic Journal: Economic Policy* **14**:3, 128-165. [Abstract] [View PDF article] [PDF with links]
23. Heather Brown, Huasheng Xiang, Viviana Albani, Louis Goffe, Nasima Akhter, Amelia Lake, Stewart Sorrell, Emma Gibson, John Wildman. 2022. No new fast-food outlets allowed! Evaluating the effect of planning policy on the local food environment in the North East of England. *Social Science & Medicine* **306**, 115126. [Crossref]
24. Joel Cuffey, Timothy K. M. Beatty. 2022. Effects of competing food desert policies on store format choice among SNAP participants. *American Journal of Agricultural Economics* **104**:4, 1485-1511. [Crossref]
25. María Pineros-Leano, Natalie Grafft, Liliana Aguayo. 2022. Childhood obesity risk factors by race and ethnicity. *Obesity* **30**:8, 1670-1680. [Crossref]
26. Céline Bonnet, Cécile Détang-Dessendre, Valérie Orozco, Elodie Rouvière. 2022. Spatial spillovers, living environment and obesity in France: Evidence from a spatial econometric framework. *Social Science & Medicine* **305**, 114999. [Crossref]
27. Katie Alegria, Sara Fleszar-Pavlović, Jacqueline Hua, Maria Ramirez Loyola, Hope Reuschel, Anna V. Song. 2022. How Socioeconomic Status and Acculturation Relate to Dietary Behaviors Within Latino Populations. *American Journal of Health Promotion* **36**:3, 450-457. [Crossref]
28. Hung-Hao Chang, Brian Lee. 2022. The association between food outlet accessibility and market competition to household food expenditures: Empirical evidence from the convenience store industry in Taiwan. *Agribusiness* **38**:1, 134-153. [Crossref]
29. Scott Kirkman, Bruce Hollingsworth, Amelia Lake, Stephanie Hinke, Stewart Sorrell, Thomas Burgoine, Heather Brown. 2021. Field validity and spatial accuracy of Food Standards Agency Food Hygiene Rating scheme data for England. *Journal of Public Health* **43**:4, e720-e727. [Crossref]
30. Bongkyun Kim, Michael R. Thomsen, Rodolfo M. Nayga, Anthony Goudie. 2021. The effect of gender-specific labor market conditions on children's weight. *Health Economics Review* **11**:1. . [Crossref]

31. Christoph Strupat, Gabriela Farfán, Laura Moritz, Mario Negre, Renos Vakis. 2021. Obesity and food away from home: What drives the socioeconomic gradient in excess body weight?. *Economics & Human Biology* **43**, 101048. [Crossref]
32. Kristin Kiesel, Mengxin Ji. 2021. Did state-mandated restrictions on sugar-sweetened drinks in California high schools increase soda purchases in school neighborhoods?. *Applied Economic Perspectives and Policy* **43**:4, 1443-1475. [Crossref]
33. Chloe C. Dedryver, Cécile Knai. 2021. 'It's Easily the Lowest I've Ever, Ever Got to': A Qualitative Study of Young Adults' Social Isolation during the COVID-19 Lockdowns in the UK. *International Journal of Environmental Research and Public Health* **18**:22, 11777. [Crossref]
34. Rodrigo Aranda, Michael Darden, Donald Rose. 2021. Measuring the impact of calorie labeling: The mechanisms behind changes in obesity. *Health Economics* **30**:11, 2858-2878. [Crossref]
35. Nasser Hadal Alotaibi, Abdulaziz I. Alzarea, Nabeel K. Alruwaili, Dibya sundar panda, Mohamed A. Abdulwahab, Mohammed Gamal, M. El Sanea Mohemed, Ehab M. Mostafa, Mohamed M. Rowezak. 2021. Awareness among Saudi Arabian parents of the relationship between Monosodium Glutamate intake and increasing Body Weight. *Research Journal of Pharmacy and Technology* 5270-5273. [Crossref]
36. Chen Zhen. 2021. Food Deserts: Myth or Reality?. *Annual Review of Resource Economics* **13**:1, 109-129. [Crossref]
37. Ahmadreza Rasouli, Sara Mohiti, Maryam Javadi, Asieh Panjeshahin, Morteza Kazemi, Mohammad Reza Shiri-Shahsavar. 2021. The effect of daily fast food consumption, family size, weight-caused stress, and sleep quality on eating disorder risk in teenagers. *Sleep and Breathing* **25**:3, 1527-1533. [Crossref]
38. Chenyang Wang, Zhiping Zhen, Nan Zhao, Chenlin Zhao. 2021. Associations between Fast-Food Restaurants Surrounding Kindergartens and Childhood Obesity: Evidence from China. *International Journal of Environmental Research and Public Health* **18**:17, 9334. [Crossref]
39. Nancy Kong, Weina Zhou. 2021. The curse of modernization? Western fast food and Chinese children's weight. *Health Economics* **30**:10, 2345-2366. [Crossref]
40. Waris Ali, Yu Danni, Badar Latif, Rehana Kouser, Saleh Baqader. 2021. Corporate Social Responsibility and Customer Loyalty in Food Chains—Mediating Role of Customer Satisfaction and Corporate Reputation. *Sustainability* **13**:16, 8681. [Crossref]
41. Heather Brown, Scott Kirkman, Viviana Albani, Louis Goffe, Nasima Akhter, Bruce Hollingsworth, Stephanie von Hinke, Amelia Lake. 2021. The impact of school exclusion zone planning guidance on the number and type of food outlets in an English local authority: A longitudinal analysis. *Health & Place* **70**, 102600. [Crossref]
42. Charles Courtemanche, Joshua C. Pinkston, Jay Stewart. 2021. Time spent exercising and obesity: An application of Lewbel's instrumental variables method. *Economics & Human Biology* **41**, 100940. [Crossref]
43. Chandra K. Dhakal, Savin Khadka. 2021. Heterogeneities in Consumer Diet Quality and Health Outcomes of Consumers by Store Choice and Income. *Nutrients* **13**:4, 1046. [Crossref]
44. Shooshan Danagoulian, Derek Jenkins. 2021. Rolling back the gains: Maternal stress undermines pregnancy health after Flint's water switch. *Health Economics* **30**:3, 564-584. [Crossref]
45. Olayinka Akanle. 2021. Gender and fast food in Nigeria and South Africa. *African Identities* **19**:1, 1-16. [Crossref]

46. Samia Badji, Nicole Black, David W. Johnston. 2020. Association between density of gaming venues in a geographical area and prevalence of insolvency: longitudinal evidence from Australia. *Addiction* **115**:12, 2349-2356. [Crossref]

47. Pierre Dubois, Rachel Griffith, Martin O'Connell. 2020. How Well Targeted Are Soda Taxes?. *American Economic Review* **110**:11, 3661-3704. [Abstract] [View PDF article] [PDF with links]

48. Wendy J Umberger, Jesmin A Rupa, Di Zeng. 2020. Understanding food westernisation and other contemporary drivers of adult, adolescent and child nutrition quality in urban Vietnam. *Public Health Nutrition* **23**:14, 2571-2583. [Crossref]

49. Pasquale E. Rummo, Erilia Wu, Zachary T. McDermott, Amy Ellen Schwartz, Brian Elbel. 2020. Relationship between retail food outlets near public schools and adolescent obesity in New York City. *Health & Place* **65**, 102408. [Crossref]

50. Jeehee Han, Amy Ellen Schwartz, Brian Elbel. 2020. Does proximity to fast food cause childhood obesity? Evidence from public housing. *Regional Science and Urban Economics* **84**, 103565. [Crossref]

51. Shawna L McNally, Stephanie Anzman-Frasca, Kelly Bowman, Mariana Beleche, Sara C Folta, Anjali A Patel. 2020. Using fundraising incentives and point-of-purchase nutrition promotion to improve food choices among school families in restaurants: a pilot and feasibility study. *Public Health Nutrition* **23**:11, 2006-2015. [Crossref]

52. Olivier Deschenes, Huixia Wang, Si Wang, Peng Zhang. 2020. The effect of air pollution on body weight and obesity: Evidence from China. *Journal of Development Economics* **145**, 102461. [Crossref]

53. Prince Kwaku Akowuah, Emmanuel Kobia-Acquah. 2020. Childhood Obesity and Overweight in Ghana: A Systematic Review and Meta-Analysis. *Journal of Nutrition and Metabolism* **2020**, 1-11. [Crossref]

54. Ahmad Albalawi, Catherine Hambly, John Speakman. 2020. Associations of Food Outlet Densities with Obesity Measures Identify Fish and Chip Shops as a Uniquely Important Problem. *Nutrients* **12**:4, 890. [Crossref]

55. Mika Matsuzaki, Brisa N. Sánchez, Maria Elena Acosta, Jillian Botkin, Emma V. Sanchez-Vaznaugh. 2020. Food environment near schools and body weight—A systematic review of associations by race/ethnicity, gender, grade, and socio-economic factors. *Obesity Reviews* **21**:4. . [Crossref]

56. Bongkyun Kim, Michael R. Thomsen, Rodolfo M. Nayga, Di Fang, Anthony Goudie. 2020. MOVE MORE, GAIN LESS: EFFECT OF A RECREATIONAL TRAIL SYSTEM ON CHILDHOOD BMI. *Contemporary Economic Policy* **38**:2, 270-288. [Crossref]

57. Rachel Griffith, Martin O'Connell, Kate Smith, Rebekah Stroud. 2020. What's on the Menu? Policies to Reduce Young People's Sugar Consumption. *Fiscal Studies* **41**:1, 165-197. [Crossref]

58. Daniel Defago, José Fernando Geng, Oswaldo Molina, Diego Santa María. 2020. Can traffic light nutritional labels induce healthier consumer choices? Experimental evidence from a developing country. *International Journal of Consumer Studies* **44**:2, 151-161. [Crossref]

59. Alessia Cavaliere, Elena Siletti, Alessandro Banterle. 2020. Nutrition information, Mediterranean diet, and weight: A structural equation approach. *Agricultural Economics (Zemědělská ekonomika)* **66**:1, 10-18. [Crossref]

60. Rebecca Taylor. 2020. It's in the Bag? The Effect of Plastic Carryout Bag Bans on Where and What People Purchase to Eat. *SSRN Electronic Journal* . [Crossref]

61. Osea Giuntella, Matthias Rieger, Lorenzo Rotunno. 2020. Weight gains from trade in foods: Evidence from Mexico. *Journal of International Economics* **122**, 103277. [Crossref]

62. Brian Elbel, Kosuke Tamura, Zachary T. McDermott, Erilia Wu, Amy Ellen Schwartz. 2020. Childhood Obesity and the Food Environment: A Population-Based Sample of Public School Children in New York City. *Obesity* **28**:1, 65-72. [Crossref]

63. Bhagyashree Katare, Sanchita Chakrovorty. 2019. Association between environmental factors and BMI: evidence from recent immigrants from developing countries. *Journal of Health, Population and Nutrition* **38**:1. . [Crossref]

64. Terri Friedline, Ian M. Dunham, Megan O'Brien. 2019. The Financial Services Environment and Schools' Savings Rates in the San Francisco Kindergarten to College Program. *Journal of Consumer Affairs* **53**:4, 1797-1824. [Crossref]

65. Jihee Choi, Soobin Seo. 2019. When a stigmatized brand is doing good. *International Journal of Contemporary Hospitality Management* **31**:9, 3447-3464. [Crossref]

66. Lauren Chenarides, Edward C. Jaenicke. 2019. Documenting the Link Between Poor Food Access and Less Healthy Product Assortment Across the U.S. *Applied Economic Perspectives and Policy* **41**:3, 434-474. [Crossref]

67. Yao Lu, David J. G. Slusky. 2019. The Impact of Women's Health Clinic Closures on Fertility. *American Journal of Health Economics* **5**:3, 334-359. [Crossref]

68. Mst. Momena Akhter. 2019. Consumer Attitude toward Fast Food Consumption: A Study on University Students in Dhaka City. *Asian Journal of Humanity, Art and Literature* **6**:1, 21-32. [Crossref]

69. Brian Elbel, Kosuke Tamura, Zachary T. McDermott, Dustin T. Duncan, Jessica K. Athens, Erilia Wu, Tod Mijanovich, Amy Ellen Schwartz. 2019. Disparities in food access around homes and schools for New York City children. *PLOS ONE* **14**:6, e0217341. [Crossref]

70. Di Zeng, Michael R. Thomsen, Rodolfo M. Nayga, Judy L. Bennett. 2019. Supermarket access and childhood bodyweight: Evidence from store openings and closings. *Economics & Human Biology* **33**, 78-88. [Crossref]

71. Jebaraj Asirvatham, Michael R. Thomsen, Rodolfo M. Nayga, Anthony Goudie. 2019. Do fast food restaurants surrounding schools affect childhood obesity?. *Economics & Human Biology* **33**, 124-133. [Crossref]

72. Hung-Hao Chang, Chad D. Meyerhoefer. 2019. Inter-brand competition in the convenience store industry, store density and healthcare utilization. *Journal of Health Economics* **65**, 117-132. [Crossref]

73. Matthew C. Harris. 2019. THE IMPACT OF BODY WEIGHT ON OCCUPATIONAL MOBILITY AND CAREER DEVELOPMENT. *International Economic Review* **60**:2, 631-660. [Crossref]

74. Alicia Izquierdo-Yusta, Carmen M. Gómez-Cantó, Jorge Pelegrin-Borondo, María Pilar Martínez-Ruiz. 2019. Consumers' behaviour in fast-food restaurants: a food value perspective from Spain. *British Food Journal* **121**:2, 386-399. [Crossref]

75. Di Zeng, Michael R. Thomsen, Rodolfo M. Nayga, Heather L. Rouse. 2019. Neighbourhood convenience stores and childhood weight outcomes: an instrumental variable approach. *Applied Economics* **51**:3, 288-302. [Crossref]

76. Michael L. Anderson, Justin Gallagher, Elizabeth Ramirez Ritchie. 2018. School meal quality and academic performance. *Journal of Public Economics* **168**, 81-93. [Crossref]

77. Bhagyashree Katare, Timothy K. M. Beatty. 2018. Do environmental factors drive obesity? Evidence from international graduate students. *Health Economics* **27**:10, 1567-1593. [Crossref]
78. Adenantera Dwicaksono, Ian Brissette, Guthrie S. Birkhead, Christine T. Bozlak, Erika G. Martin. 2018. Evaluating the Contribution of the Built Environment on Obesity Among New York State Students. *Health Education & Behavior* **45**:4, 480-491. [Crossref]
79. Mary T. Gorski Findling, Julia A. Wolfson, Eric B. Rimm, Sara N. Bleich. 2018. Differences in the Neighborhood Retail Food Environment and Obesity Among US Children and Adolescents by SNAP Participation. *Obesity* **26**:6, 1063-1071. [Crossref]
80. Gabriel Schwartz, Todd Grindal, Parke Wilde, Jacob Klerman, Susan Bartlett. 2018. Supermarket Shopping and The Food Retail Environment among SNAP Participants. *Journal of Hunger & Environmental Nutrition* **13**:2, 154-179. [Crossref]
81. Rebecca Lindberg, Abbey C Sidebottom, Brigitte McCool, Raquel F Pereira, Arthur Sillah, Jackie L Boucher. 2018. Changing the restaurant food environment to improve cardiovascular health in a rural community: implementation and evaluation of the Heart of New Ulm restaurant programme. *Public Health Nutrition* **21**:5, 992-1001. [Crossref]
82. Yeonsoo Kim, Mari Luz Zapata Ramos. 2018. Stakeholder responses toward fast food chains' CSR. *Corporate Communications: An International Journal* **23**:1, 117-138. [Crossref]
83. Michal Stoklosa, Kerem Shuval, Jeffrey Drope, Rusty Tchernis, Mark Pachucki, Amy Yaroch, Matthew Harding. 2018. The intergenerational transmission of obesity: The role of time preferences and self-control. *Economics & Human Biology* **28**, 92-106. [Crossref]
84. Hunt mname Allcott, Rebecca mname Diamond, Jean-Pierre mname Dubb. 2018. The Geography of Poverty and Nutrition: Food Deserts and Food Choices Across the United States. *SSRN Electronic Journal* . [Crossref]
85. Nancy Kong, Weina Zhou. 2018. The Massive Expansion of Western Fast-Food Restaurants and Children's Weight in China. *SSRN Electronic Journal* . [Crossref]
86. Marit Hinnosaar. 2018. How Long Do Healthy Habits Last? The Role of Prices. *SSRN Electronic Journal* **134**. . [Crossref]
87. Ram Orzach. 2018. Supersizing: The Illusion of a Bargain and the Right-to-Split. *SSRN Electronic Journal* . [Crossref]
88. Amal Bakr Shori, Mai Albaik, Fardos M. Bokhari. 2017. Fast food consumption and increased body mass index as risk factors for weight gain and obesity in Saudi Arabia. *Obesity Medicine* **8**, 1-5. [Crossref]
89. Keith Barnatchez, Leland D. Crane, Ryan A. Decker. 2017. An Assessment of the National Establishment Time Series (NETS) Database. *Finance and Economics Discussion Series* **2017**:110. . [Crossref]
90. Brandon J. Restrepo. 2017. Calorie Labeling in Chain Restaurants and Body Weight: Evidence from New York. *Health Economics* **26**:10, 1191-1209. [Crossref]
91. R. Salehnejad, R. Allmendinger, Y.-W. Chen, M. Ali, A. Shahgholian, P. Yiapanis, M. Mansur. Leveraging data mining techniques to understand drivers of obesity 1-9. [Crossref]
92. Shannon N. Zenk, Elizabeth Tarlov, Coady Wing, Stephen A. Matthews, Kelly Jones, Hao Tong, Lisa M. Powell. 2017. Geographic Accessibility Of Food Outlets Not Associated With Body Mass Index Change Among Veterans, 2009–14. *Health Affairs* **36**:8, 1433-1442. [Crossref]
93. Mohsen Mazidi, John R Speakman. 2017. Higher densities of fast-food and full-service restaurants are not associated with obesity prevalence. *The American Journal of Clinical Nutrition* **106**:2, 603-613. [Crossref]

94. Meliyanni Johar, Shiko Maruyama, Jeffrey Truong. 2017. The contribution of Western fast food to fast-growing body mass in China. *Applied Economics* **49**:8, 797-811. [Crossref]
95. Viachaslau Filimonau, Christian Lemmer, David Marshall, Gisel Bejjani. 2017. 'Nudging' as an architect of more responsible consumer choice in food service provision: The role of restaurant menu design. *Journal of Cleaner Production* **144**, 161-170. [Crossref]
96. Patricia M. Anderson, Kristin F. Butcher, Diane Whitmore Schanzenbach. 2017. Adequate (or Adipose?) Yearly Progress: Assessing the Effect of "No Child Left Behind" on Children's Obesity. *Education Finance and Policy* **12**:1, 54-76. [Crossref]
97. Ariadna Jou, NNria Mas, Carles Vergara-Alert. 2017. The Effects of Wealth on Health. Micro-Evidence from Homeowners' Housing Wealth Misestimation. *SSRN Electronic Journal* . [Crossref]
98. Linlin Fan. 2017. Access to Fruits and Vegetables and Consumer Welfare in Urban Food Deserts. *SSRN Electronic Journal* . [Crossref]
99. Joseph J. Sabia, Jeffrey Swigert, Timothy Young. 2017. The Effect of Medical Marijuana Laws on Body Weight. *Health Economics* **26**:1, 6-34. [Crossref]
100. Xun Li, Rigoberto A. Lopez. 2016. Food environment and weight outcomes: a stochastic frontier approach. *Applied Economics* **48**:47, 4526-4537. [Crossref]
101. Julian M. Alston, Joanna P. MacEwan, Abigail M. Okrent. 2016. The Economics of Obesity and Related Policy. *Annual Review of Resource Economics* **8**:1, 443-465. [Crossref]
102. Stella G Uzogara. 2016. Assessment of Obesity, Presumed and Proven Causes and Prevention Strategies: A Review. *Advances in Obesity, Weight Management & Control* **5**:1. . [Crossref]
103. Mohammad Hajizadeh, M. Karen Campbell, Sisira Sarma. 2016. A Spatial Econometric Analysis of Adult Obesity: Evidence from Canada. *Applied Spatial Analysis and Policy* **9**:3, 329-363. [Crossref]
104. Asli Ucar, Serkan Yilmaz, Ezgi Karatas, Yahya Ozdogan. 2016. Genetic alterations and nutritional habits among fast-food employees. *Toxicology and Environmental Health Sciences* **8**:3, 213-220. [Crossref]
105. Shirlee Lichtman-Sadot. 2016. Does banning carbonated beverages in schools decrease student consumption?. *Journal of Public Economics* **140**, 30-50. [Crossref]
106. . Chronic Diseases 21-42. [Crossref]
107. Sidharth Muralidharan. 2016. Spoofing: social commentary or effective marketing tool? Testing promotion vs. prevention message frames in college students' fight against obesity. *Social Influence* **11**:3, 151-165. [Crossref]
108. Aneel Karnani, Brent McFerran, Anirban Mukhopadhyay. 2016. The Obesity Crisis as Market Failure: An Analysis of Systemic Causes and Corrective Mechanisms. *Journal of the Association for Consumer Research* **1**:3, 445-470. [Crossref]
109. Rebecca Taylor, Sofia B. Villas-Boas. 2016. Food Store Choices of Poor Households: A Discrete Choice Analysis of the National Household Food Acquisition and Purchase Survey (FoodAPS). *American Journal of Agricultural Economics* **98**:2, 513-532. [Crossref]
110. Else Gry Bro Christensen, Julia Nafziger. 2016. Packaging of sin goods – Commitment or exploitation?. *Journal of Economic Behavior & Organization* **122**, 62-74. [Crossref]
111. Ram Orzach, Miron Stano. 2016. Supersizing: The Illusion of a Bargain and the Right-to-Split. *SSRN Electronic Journal* . [Crossref]

112. Raymond J. March, Conrad Lyford, Carlos E. Carpio, Tullaya Boonsaeng. 2016. Do SNAP Recipients Get the Best Prices?. *SSRN Electronic Journal* . [Crossref]

113. Tanya K. Kaufman, Daniel M. Sheehan, Andrew Rundle, Kathryn M. Neckerman, Michael D. M. Bader, Darby Jack, Gina S. Lovasi. 2015. Measuring health-relevant businesses over 21 years: refining the National Establishment Time-Series (NETS), a dynamic longitudinal data set. *BMC Research Notes* **8**:1. . [Crossref]

114. Christopher S. Carpenter, D. Sebastian Tello-Trillo. 2015. Do Cheeseburger Bills Work? Effects of Tort Reform for Fast Food. *The Journal of Law and Economics* **58**:4, 805-827. [Crossref]

115. Laura Tach, Mariana Amorim. 2015. Constrained, Convenient, and Symbolic Consumption: Neighborhood Food Environments and Economic Coping Strategies among the Urban Poor. *Journal of Urban Health* **92**:5, 815-834. [Crossref]

116. France Caillavet, Gayaneh Kyureghian, Rodolfo M. Nayga, Coline Ferrant, Pierre Chauvin. 2015. Does Healthy Food Access Matter in a French Urban Setting?. *American Journal of Agricultural Economics* **97**:5, 1400-1416. [Crossref]

117. Cheng Chen, Shin-Yi Chou, Robert J. Thornton. 2015. The Effect of Household Technology on Weight and Health Outcomes among Chinese Adults: Evidence from China's "Home Appliances Going to the Countryside" Policy. *Journal of Human Capital* **9**:3, 364-401. [Crossref]

118. Julianne Williams, Peter Scarborough, Nick Townsend, Anne Matthews, Thomas Burgoine, Lorraine Mumtaz, Mike Rayner. 2015. Associations between Food Outlets around Schools and BMI among Primary Students in England: A Cross-Classified Multi-Level Analysis. *PLOS ONE* **10**:7, e0132930. [Crossref]

119. Laura Nixon, Pamela Mejia, Lori Dorfman, Andrew Cheyne, Sandra Young, Lissy C. Friedman, Mark A. Gottlieb, Heather Wooten. 2015. Fast-Food Fights: News Coverage of Local Efforts to Improve Food Environments Through Land-Use Regulations, 2000–2013. *American Journal of Public Health* **105**:3, 490-496. [Crossref]

120. James Niels Rosenquist, Steven F. Lehrer, A. James O'Malley, Alan M. Zaslavsky, Jordan W. Smoller, Nicholas A. Christakis. 2015. Cohort of birth modifies the association between FTO genotype and BMI. *Proceedings of the National Academy of Sciences* **112**:2, 354-359. [Crossref]

121. Alessandro Banterle, Alessia Cavaliere. 2014. Is there a relationship between product attributes, nutrition labels and excess weight? Evidence from an Italian region. *Food Policy* **49**, 241-249. [Crossref]

122. Mouhcine Guettabi, Abdul Munasib. 2014. "Space Obesity": The Effect of Remoteness on County Obesity. *Growth and Change* **45**:4, 518-548. [Crossref]

123. Deirdre A. Dingman, Mark R. Schulz, David L. Wyrick, Daniel L. Bibeau, Sat N. Gupta. 2014. Factors Related to the Number of Fast Food Meals Obtained by College Meal Plan Students. *Journal of American College Health* **62**:8, 562-569. [Crossref]

124. Kevin M. Fitzpatrick, Don Willis, Gail O'Connor. 2014. Circumstances, Resources, and Weight Status Outcomes Among Middle School Students. *The Journal of Early Adolescence* **34**:8, 1058-1074. [Crossref]

125. Penny Gordon-Larsen. 2014. Food Availability/Convenience and Obesity. *Advances in Nutrition* **5**:6, 809-817. [Crossref]

126. Mouhcine Guettabi, Abdul Munasib. 2014. URBAN SPRAWL, OBESOGENIC ENVIRONMENT, AND CHILD WEIGHT. *Journal of Regional Science* **54**:3, 378-401. [Crossref]

127. J. Williams, P. Scarborough, A. Matthews, G. Cowburn, C. Foster, N. Roberts, M. Rayner. 2014. A systematic review of the influence of the retail food environment around schools on obesity-related outcomes. *Obesity Reviews* **15**:5, 359-374. [Crossref]

128. T. J. Richards, L. Mancino. 2014. Demand for food-away-from-home: a multiple-discrete-continuous extreme value model. *European Review of Agricultural Economics* **41**:1, 111-133. [Crossref]

129. Karen S. Hamrick, Abigail Okrent. 2014. The Role of Time in Fast-Food Purchasing Behavior in the United States. *SSRN Electronic Journal* . [Crossref]

130. Eojina Kim, Sunny Ham, Il Sun Yang, Jeong Gil Choi. 2013. The roles of attitude, subjective norm, and perceived behavioral control in the formation of consumers' behavioral intentions to read menu labels in the restaurant industry. *International Journal of Hospitality Management* **35**, 203-213. [Crossref]

131. Tracy K. Richmond, Jennifer L. Spadano-Gasbarro, Courtney E. Walls, S. Bryn Austin, Mary L. Greaney, Monica L. Wang, Solomon Mezegebu, Karen E. Peterson. 2013. Middle school food environments and racial/ethnic differences in sugar-sweetened beverage consumption: Findings from the Healthy Choices study. *Preventive Medicine* **57**:5, 735-738. [Crossref]

132. Georgia S. Papoutsi, Andreas C. Drichoutis, Rodolfo M. Nayga. 2013. THE CAUSES OF CHILDHOOD OBESITY: A SURVEY. *Journal of Economic Surveys* **27**:4, 743-767. [Crossref]

133. Susan Elizabeth Chen, Raymond J. Florax, Samantha D. Snyder. 2013. Obesity and fast food in urban markets: a new approach using geo-referenced micro data. *Health Economics* **22**:7, 835-856. [Crossref]

134. Sonya Grier, Brennan Davis. 2013. Are All Proximity Effects Created Equal? Fast Food near Schools and Body Weight among Diverse Adolescents. *Journal of Public Policy & Marketing* **32**:1, 116-128. [Crossref]

135. Chad Cotti, Nathan Tefft. 2013. Fast food prices, obesity, and the minimum wage. *Economics & Human Biology* **11**:2, 134-147. [Crossref]

136. Yang Wang, Muzhe Yang. 2013. Crisis-induced depression, physical activity and dietary intake among young adults: Evidence from the 9/11 terrorist attacks. *Economics & Human Biology* **11**:2, 206-220. [Crossref]

137. Pedro A. Alviola, Rodolfo M. Nayga, Michael Thomsen. 2013. Food Deserts and Childhood Obesity. *Applied Economic Perspectives and Policy* **35**:1, 106-124. [Crossref]

138. Randall Akee,, Emilia Simeonova,, William Copeland,, Adrian Angold,, E. Jane Costello. 2013. Young Adult Obesity and Household Income: Effects of Unconditional Cash Transfers. *American Economic Journal: Applied Economics* **5**:2, 1-28. [Abstract] [View PDF article] [PDF with links]

139. Josh C. Bongard, Paul D. H. Hines, Dylan Conger, Peter Hurd, Zhenyu Lu. 2013. Crowdsourcing Predictors of Behavioral Outcomes. *IEEE Transactions on Systems, Man, and Cybernetics: Systems* **43**:1, 176-185. [Crossref]

140. Cass R. Sunstein. 2013. Nudges.gov: Behavioral Economics and Regulation. *SSRN Electronic Journal* . [Crossref]

141. Thomas G. Koch, Nathan Wilson. 2013. Decomposing the American Obesity Epidemic. *SSRN Electronic Journal* . [Crossref]

142. Cass R. Sunstein. 2013. Behavioral Economics, Consumption, and Environmental Protection. *SSRN Electronic Journal* . [Crossref]

143. Laurian J. Unnevehr. 2013. Food and Health: Can Economics Contribute to Improved Outcomes?. *American Journal of Agricultural Economics* **95**:2, 220-227. [Crossref]

144. Nicole L. Novak, Kelly D. Brownell. 2012. Role of Policy and Government in the Obesity Epidemic. *Circulation* **126**:19, 2345-2352. [Crossref]

145. Pierre Chandon, Brian Wansink. 2012. Does food marketing need to make us fat? A review and solutions. *Nutrition Reviews* **70**:10, 571-593. [Crossref]

146. George L. Wehby, Charles J. Courtemanche. 2012. The heterogeneity of the cigarette price effect on body mass index. *Journal of Health Economics* **31**:5, 719-729. [Crossref]

147. Andreas C. Drichoutis, Rodolfo M. Nayga, Panagiotis Lazaridis. 2012. Food away from home expenditures and obesity among older Europeans: are there gender differences?. *Empirical Economics* **42**:3, 1051-1078. [Crossref]

148. Helen Lee. 2012. The role of local food availability in explaining obesity risk among young school-aged children. *Social Science & Medicine* **74**:8, 1193-1203. [Crossref]

149. Ryan D. Edwards. 2012. Sugar-sweetened beverage taxes raise demand for substitutes and could even raise caloric intake. *Preventive Medicine* **54**:3-4, 284-285. [Crossref]

150. Charles Courtemanche, Garth Heutel, Patrick McAlvanah. 2012. Impatience, Incentives, and Obesity. *SSRN Electronic Journal* **27**. . [Crossref]

151. Delia Furtado, Nikolaos Theodoropoulos. 2012. Immigrant Networks and the Take-Up of Disability Programs: Evidence from U.S. Census Data. *SSRN Electronic Journal* . [Crossref]

152. Aparna Lhila. 2011. Does access to fast food lead to super-sized pregnant women and whopper babies?. *Economics & Human Biology* **9**:4, 364-380. [Crossref]

153. Philip H Howard, Margaret Fitzpatrick, Brian Fulfrost. 2011. Proximity of food retailers to schools and rates of overweight ninth grade students: an ecological study in California. *BMC Public Health* **11**:1. . [Crossref]

154. Ming Li, Michael J Dibley, Hong Yan. 2011. School environment factors were associated with BMI among adolescents in Xi'an City, China. *BMC Public Health* **11**:1. . [Crossref]

155. Richard A. Dunn, Joseph R. Sharkey, Scott Horel. 2011. The effect of fast-food availability on fast-food consumption and obesity among rural residents: An analysis by race/ethnicity. *Economics & Human Biology* . [Crossref]

156. Melissa Ahern, Cheryl Brown, Stephen Dukas. 2011. A National Study of the Association Between Food Environments and County-Level Health Outcomes. *The Journal of Rural Health* **27**:4, 367-379. [Crossref]

157. Cindy W. Leung, Barbara A. Laraia, Maggi Kelly, Dana Nickleach, Nancy E. Adler, Lawrence H. Kushi, Irene H. Yen. 2011. The Influence of Neighborhood Food Stores on Change in Young Girls' Body Mass Index. *American Journal of Preventive Medicine* **41**:1, 43-51. [Crossref]

158. John Tomer. 2011. What Causes Obesity? And Why Has It Grown So Much?. *Challenge* **54**:4, 22-49. [Crossref]

159. Charles Courtemanche, Art Carden. 2011. Supersizing supercenters? The impact of Walmart Supercenters on body mass index and obesity. *Journal of Urban Economics* **69**:2, 165-181. [Crossref]

160. Bryan Bollinger,, Phillip Leslie,, Alan Sorensen. 2011. Calorie Posting in Chain Restaurants. *American Economic Journal: Economic Policy* **3**:1, 91-128. [Abstract] [View PDF article] [PDF with links]

161. Michael L. Anderson,, David A. Matsa. 2011. Are Restaurants Really Supersizing America?. *American Economic Journal: Applied Economics* **3**:1, 152-188. [Abstract] [View PDF article] [PDF with links]

162. Richard A. Dunn. 2010. The Effect of Fast-Food Availability on Obesity: An Analysis by Gender, Race, and Residential Location. *American Journal of Agricultural Economics* **92**:4, 1149-1164. [Crossref]

163. Charles Courtemanche, Art Carden. 2010. Supersizing Supercenters? The Impact of Wal-Mart Supercenters on Body Mass Index and Obesity. *SSRN Electronic Journal* . [Crossref]

164. John F. Tomer. 2010. What Causes Obesity? And Why has it Grown so Much? An Alternative View. *SSRN Electronic Journal* . [Crossref]