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Stress in the desert:
Estimating the relationship among diet quality, allostatic load and food access

Lisa Mancino and Michele Ver Ploeg[†]
Economic Research Service, USDA

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[†]The opinions expressed here are those of the authors and cannot be attributed to the Economic Research Service or the U. S. Department of Agriculture.

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Introduction

While poor diet quality and excess bodyweight are a problem for many Americans, there are significant health disparities across socioeconomic, racial and ethnic subgroups. To better understand why these disparities exist and persist, researchers and policymakers have turned their attention to understanding how the food environment affects diet and health. The bulk of attention has focused on lower income neighborhoods with limited access to supermarkets, supercenters, grocery stores, or other sources of healthy and affordable food. Individuals in these neighborhoods may find it more difficult to eat a healthy diet because healthful foods may be harder to obtain, more expensive or both, while less healthful, energy-dense foods may be more accessible and relatively less expensive. For example, the time-cost of obtaining healthy foods in a neighborhood with low food access be higher than it is for those living within walking distance to a supermarket. The monetary cost of certain healthful foods, such as fresh produce and whole grain breads, may also be higher in areas where supermarkets and larger food retailers are scarce, but smaller retailers that usually sell only a limited selection of such foods, are plentiful. As a result, differences in relative costs may encourage individuals in areas with low food access to choose less-healthy diets.

To address this issue, the U.S. Congress has proposed the Healthy Food Finance Initiative to build upon State and local programs already in existence. These programs assume that if healthier foods are more readily available, residents of low-income and underserved neighborhoods will improve their diets in the short-run and their overall health status in the long-run. However, it may be that the lack of access to healthier food retailers is the result of

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lower demand for healthy foods. For one, individuals who are more interested in having easy access to healthful foods may choose to live in neighborhoods with better food access. Additionally, stores choose where to locate based on perceived demand for healthful foods. One possible reason for a lower demand for healthy foods may be that choosing a healthier diet requires some immediate tradeoffs—possibly in terms of money, time or taste—for possible better health in the future and individuals who are more present-biased may simply choose not make these tradeoffs.

Another possible reason why demand for healthy foods is lower in low income neighborhoods may be that living in lower income neighborhoods is associated with additional stressors that lead to competing demands for one's attention. Studies have shown that lower income neighborhoods are associated with higher levels of unemployment, crowding, substandard housing, violence and crime (Evans and English, 2003). These factors could in turn make it difficult for nutrition and diet quality to remain top of mind. Recent research on the effects of living in a poor neighborhood on health has analyzed the effects of poor conditions on biological and physiological markers of chronic stress (Massey, 2004; Hill et al., 2005). These studies build upon work that argues that residents of poor neighborhoods suffer physiological costs of chronic exposure to stressful situations and that these physiological burdens can be measured through allostatic load (AL) (McEwan, 2000).

Thus, it is important to isolate these demand side factors to better assess the likely impact of public efforts to make healthy foods more available in low access neighborhoods. While past studies have examined the relationship between neighborhood access to food retailers and diet-related outcomes, much of the existing literature on this topic has been

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limited to selected localities or subsets of the U.S. population (see Larson et al., 2009 for a review of this literature). In this research, we use nationally representative data on individual's diet and health from multiple rounds the National Health and Nutrition Examination Survey, from 2003-2008, merged with data on the local food access for the entire nation.

While the cross-sectional nature of this data limitations our ability to establish a causal relationship between food access and diet quality, we use the richness of the data on diet, behavior, stress and socioeconomic status available in the survey to create comparisons of diet quality outcomes across groups that are as similar to each other as possible. We begin by presenting simple statistics to describe average differences between individuals living in low-access neighborhoods and those who do not. Then, propensity score matching techniques are used to limit this comparison to individuals living in food deserts and individuals that are similar to residents of food deserts on observable characteristics, such as income, age, education and race/ethnicity. We then add additional control variables to better isolate the impact of living in a low access neighborhood. The relationship between food access and other behaviors that may indicate more present-biased preferences, such as cigarette smoking, binge drinking and drug use is examined.

We also attempt to isolate the effect of living in a low access neighborhood from the effect of stress. To examine the sensitivity of the estimated relationship between diet quality and neighborhood food access, we also run a series of estimates that take an individual's exposure to chronic stress as an additional matching factor. In essence, this provides an estimate of the effect of living in a neighborhood with better food access, assuming that individual has the same income, level of education and stress as she or he did when living in the

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low access neighborhood. Finally, we take a kitchen sink approach and match individuals on both our proxy for stress and our proxies for time preferences.

Previous Literature

Studies of the relationship between limited food access and dietary outcomes have shown mixed results. Early cross-sectional studies in general, found a positive relationship between diet quality and access to healthy food sources, such as supermarkets (Larson et al., 2009).[1] Cross-sectional results also suggest that greater access to supermarkets was positively associated with lower obesity levels, while greater access to convenience stores was associated with higher levels of obesity (Larson et al., 2009). These studies suggest a relationship between food deserts and diet and health outcomes, but cross-sectional data are limited in drawing more causal inferences. The cross-sectional data cannot control for the length of time that individuals live in food desert neighborhoods, which is likely to be related to the severity of the effects of food deserts. These studies are often unable to control for other characteristics of neighborhoods that may affect diet-related outcomes such as crime levels, walkability, or other environmental pollutants. Cross-sectional studies are also weak because they often do not account for unobserved factors that may affect both where residents choose to live and the importance they place on dietary health, nor a firm's decision to locate different types of stores in different neighborhoods (e.g. zoning rules, access to major transportation routes), and the spatial correlation between individuals and firms making decisions.

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[1] Supermarkets and other large food retailers such as supercenters, are often used to proxy sources of healthy foods because they usually carry a wide selection of fruits, vegetables, whole grains, low-fat dairy, and other healthy foods and on average, at lower prices (Leibtag, 2006; Kaufman et al., 1997

Recent studies have used econometric methods or longitudinal data to tease out how food access differences affect diet and health. Chen et al., (2010) uses instrumental variables and spatial econometrics to estimate the effect of supermarket proximity on BMI in the Indianapolis area. They find that the density of chain supermarkets is negatively related to BMI, although the effect is modest. There have also now been several longitudinal studies of the effect of healthy food access on diet and weight. A longitudinal study of young people age 18-30 found that diet quality was not related to the availability of supermarkets (Boone-Heinonen et al., 2011). Block et al. (2011) used a 30 year longitudinal data set from four Massachusetts communities to study the long-term relationship between food retail outlet availability and body weight. This study did not find a consistent relationship between grocery store proximity and BMI (Block, 2011). Two recent longitudinal studies have examined access to different food retailers and children's BMI with mixed results. Lee (2012) used a cohort of kindergartners and followed them through 5th grade to examine the relationship between BMI and exposure to different food retail outlets. This study found no relationship between BMI and exposure to grocery or convenience stores. Powell and Chaloupka (2009) examine the relationship between fruit and vegetable prices and food-related retail outlet availability to examine the BMI of children age 0 to 12 in 1997 and their follow-up five to six years later. This study found no relationship between BMI and food outlet availability.

These recent studies use more rigorous methods to estimate the effect of food deserts on diet and health. However, they do have limitations. Very few longitudinal studies include rich measures of dietary intake and health outcomes. If they include these measures, it is usually only in studies of segments of the population (e.g. limited age cohorts or limited

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regions). The Chen et al. study (2010) is also an advancement, but it only covers one city in the U.S. and is limited to the study of chain supermarkets (not all supermarkets).

Another complicating factor in estimating the effect of food access limitations on diet and health is in isolating the effect of food access limitations from other consequences of living in neighborhoods with few amenities and perhaps some negative amenities. In some neighborhoods, the difficulty of accessing healthy foods may have minor effects on diet and health compared with the effects or other causes of stress—such as crime, harassment or general disorder. Exposure to chronic stressful situations in some neighborhoods could cause adverse physiological and health outcomes (McEwan, 2000; Massey, 2004 and Hill et al., 2005). Chronic stress may have an independent effect on diet and thus, diet-related health if it affects food choices.

Data

For this study, we combine data on neighborhood food store access with data on dietary intake and measures of stress. Measures of neighborhood food store access were developed by the Economic Research Service (ERS) of the U.S. Department of Agriculture and are publicly available on the Food Access Research Atlas (FARA) mapping tool (ERS, 2013) as well its predecessor, the Food Desert Locator (ERS, 2011). These national level measures indicate whether a low income census tract has a significant number or share of the population with food access limitations. Food access limitations are measured by proximity to supermarkets. For example, one measure that is available for multiple years, estimates the number and percentage of people in a census tract that are more than 1 mile from a supermarket (urban

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areas) or more than 10 miles from a supermarket (rural areas). If the low-income census tract contains more than 500 people or one-third of the population with limited access, it is considered a food desert. In 2006, 6,529 US census tracts (about 10 percent of all tracts) were food deserts. This number increased in 2010 to 8,959 census tracts (or about 12 percent of all tracts), an increase that is mostly due to an increase in the number of low-income census tracts between 2006 and 2010.

For dietary intake, we use nationally representative data from multiple rounds of the National Health and Nutrition Examination Survey (NHANES), from 2003-2008. Census tract level information on food store access and other characteristics from the FARA mapping tool, (urban or rural status; low-income status) are merged to individual NHANES respondents through a restricted access data set.

We limit our analysis to low-income individuals because most Federal and local level efforts to improve food access are currently targeted at lower income neighborhoods. We also focus only on those who live in urban areas because the measure of food store access that is available for the time period covered in our study is solely based on distance to a supermarket and does not account for vehicle ownership, a factor that is likely to affect food store access considerably more in rural areas.[2] In this study, low-income is defined as having a household income that does not exceed 1.85 times the poverty threshold for that household's size and composition. We also limit our analysis to non-pregnant adults age 20 or older. This gives us a total of 3,332 observations. All summary statistics for our outcome, treatment and matching variables are presented in Table 2. We present summary statistics for the full NHANES adult

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[2] A measure that considers vehicle availability is available in the FARA, but only for 2010.

sample, our study sample and then divide the study sample by low-access status. In these last two columns, statistics reported in bold font indicate the means are significantly different at the 10% level or above.

As part of the NHANES exams, each respondent provides an in person 24-hour dietary recall, which is followed up with a second day recall over the phone, generally 3 to 10 days later. Diet quality is measured using the 2-day average daily 2005 Healthy Eating Index (HEI-2005) score, a method developed by the USDA.[3] The HEI-2005 score measures how well an individual's diet adheres to the 2005 *Dietary Guidelines for Americans*. We also examine individual components that make up this score. In particular, we estimate the correlation between neighborhood food access and the 2-day average intake of whole fruits, vegetables, whole grains, sodium, saturated fats and empty calories, which is measured as the share of daily calories a person consumes from solid fats, added sugars and alcohol.

We also examine whether there is a relationship between neighborhood access and other behaviors that may affect diet and health outcomes. We estimate whether or not there is a significant relationship between neighborhood food access and the number of meals an individual reported eating away from home over the 2 dietary intake days and the usual number of meals eaten away from home per week. These variables are examined because the time and monetary tradeoffs between preparing food at home and purchasing food away from home may also be highly influenced by the accessibility of food stores and restaurants.

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[3] The USDA has released the 2010 Dietary Guidelines and subsequent 2010 HEI score. However, the underlying databases to recalculate the 2003-2008 NHANES data are not yet publically available at this time. Thus, we use the previous, although similar, 2005 HEI score. For a summary of differences between the two HEI scores, please see tables X. which summarize the criteria used for each version.

The association between neighborhood food access and smoking habits, binge drinking episodes (defined as occasions where a respondent had 5 or more drinks in one night) and illegal drug use is also examined because these behaviors could be indicative of more present-biased time preferences. All these behaviors have well- documented adverse long term consequences, but can provide short term enjoyment. Our motivation for looking at these variables is to examine whether individuals living in low access neighborhoods indicate less concern about their future health in general or whether these differences are limited to dietary choices.

For our measure of chronic exposure to stress, we use data collected during the detailed NHANES medical examination and calculate each individual's allostatic load (AL). We use the AL measure created by Crimmins et al (1999), which includes blood pressure, glycated hemoglobin, albumin, total cholesterol, high density lipoproteins, and C-reactive protein. It is important to note this measure of chronic stress is more likely to reflect one's subjective experience of stress rather than objective exposure. While individuals may vary in how they perceive and manage various stressors, those that exhibit higher biomarker levels for stress have likely experienced higher levels of stress as well. Thus, we feel that this measure of experienced stress is appropriate for our study.

Our measure of AL uses specific cutoff levels to determine if each of the AL components is above (or below) a critical threshold. The final AL score is the number of components for which a respondent was above (or below) the threshold value. We report the cutoff thresholds for each component, the mean value for each, and the total AL scores in table 3. Again, we

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present these for the total adult NHANES population, the low-income urban population and then separate the low-income urban population by food access status.

In all of our estimates we also control for a respondent's per-person household income relative to the poverty ratio (which we refer to this as the poverty index ratio or PIR), gender, age, education, race/ethnicity and which of the 3 NHANES rounds the respondent was surveyed. Again, summary statistics for these measures are also reported in table 2.

Discussion of summary statistics to be posted after NCHS clearance

Methodology

In cross-sectional data such as the NHANES, a standard linear regression will yield biased estimates of the relationship between food access and diet quality if unobserved characteristics affect both diet and the choice of which neighborhood to live in. We attempt to reduce this bias by using propensity-score matching (PSM) techniques (Rosenbaum and Rubin, 1983, Heckman et al, 1998) to match food desert inhabitants to people who do not live in a food desert, based on their propensity scores. The propensity score is a summary measure of one's likelihood to have been "treated"—in this case, live in a food desert—based on one's observable characteristics such as income, age, gender, race, ethnicity, and educational attainment. While these are the same observables that one might employ in a standard linear model, the strength of using a PSM approach is it limits the sample from which the treatment effect is estimated so that the treated and untreated populations are more comparable. In contrast, a linear regression model does not restrict the comparison group to those who are

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otherwise similar, and may thus exaggerate the estimated effect of treatment if these factors are also correlated with the treatment effect.

In this paper, we employ both techniques and a hybrid approach that will be described below. We begin by estimating the correlation between neighborhood food access and diet quality, and other health related behaviors using a standard linear model. For our linear regression estimates, we use STATA 11.0 and account for the NHANES survey design. We then use PSM matching to obtain an alternative estimate of the impact of living in a food desert on diet quality. For this, we use STATA's psmatch2 command, and a probit model to calculate propensity scores for each individual. Propensity scores are used to identify respondents in the non-treatment group that are similar to those in the treatment group. For simplicity, we use one-to-one matching to calculate average treatment effects[4].

We also employ a hybrid approach, which uses the same linear regression model described above, but limits the linear regression sample to the same sample that was used to obtain the PSM estimates. We also adjust the NHANES sample weights to account for non-treated respondents that were used multiple times in the one-to-one matching. We use the frequency that a non-treated respondent was matched to a treated respondent and then multiply this frequency by the appropriate NHANES sample weights. This allows us to get a population level estimate of the average treatment effect. For example, if a respondent outside of the food desert was dropped from the PSM estimates, that respondent is also dropped from

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[4] We did fiddle around with other matching techniques, such as k-nearest neighbor, and radius matching. We found that our results did not change significantly. After running psmatch2, we tested the average difference in observables between the treated and untreated groups used to calculate treatment effects. Overall, our tests met the balancing criteria (reword this).

this hybrid regression approach. If a non-treated respondent was matched to two treated respondents, then the NHANES sample weights are multiplied by 2.

As mentioned above, it is possible that levels of stress may also be highly correlated with one's food environment. To examine the sensitivity of the estimated relationship between diet quality and neighborhood food access, we also run a series of estimates that use an individual's exposure to chronic stress as an additional matching factor. In essence, this provides an estimate of the effect of living in a neighborhood with better food access, assuming that individual has the same income, level of education and stress as she or he did when living in the low access neighborhood. For consistency, we follow the same approach and estimate linear regression models that also included AL scores. In the PSM estimates and hybrid PSM/regression estimates, AL scores are used as additional observables on which to match treated and non-treated respondents. We then compare these results to estimates that do not include AL scores to examine whether omitting measures of stress increases the estimated effect of food access on diet quality. We do the same for estimates that control for time preference proxies and AL as well.

Results

Results to be posted once cleared by NCHS

Discussion

Discussion to be posted once cleared by NCHS

References

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Block, J.P., N.A. Christakis, J. O'Malley, and S.V. Subramanian. 2011. "Proximity to food establishments and body mass index in the Framingham Heart Study Offspring Cohort over 30 years," American Journal of Epidemiology 174(10): 1108-1114.

Boone-Heinonen, J., P. Gordon-Larsen, C.I. Kiefe, J.M. Shikany, C.E. Lewis, and B.M. Popkin. 2011. "Fast food restaurants and food stores: Longitudinal associations with diet in young to middle-aged adults," Archives of Internal Medicine 171(13): 1162-1170.

Chen, S., R.J.G.M. Florax, and S.D. Snyder. 2010. "Does where you live make you fat? Obesity and access to chain grocers," *Economic Geography* 86(4): 431-452.

Crimmins, E. M., J.K. Kim and T.E. Seeman. 1999. "Poverty and Biological Risk: The Earlier "Aging" of the Poor." *Journal of Gerontology: Medical Sciences* 64A(2): 286-292.

Economic Research Service (ERS), U.S. Department of Agriculture (USDA) (2013). Food Access Research Atlas, http://www.ers.usda.gov/data-products/food-access-research-atlas.aspx. (Accessed on May 9, 2013).

Economic Research Service (ERS), U.S. Department of Agriculture (USDA) (2011). The Food Desert Locator, http://www.ers.usda.gov/dataFiles/Food_Access_Research_Atlas/Download_the_Data/Archived_Version/archived_documentation.pdf (Accessed on May 9, 2013).

Evans, G.W and K. English. 2003. "The Environment of Poverty: Multiple Stressor Exposure, Psychophysiological Stress, and Socioemotional Adjustment." *Child Development* 73(4): 1238-1248.

Geronimus, A.T., M. Hicken, D. Keene, and J. Bound (2006). "'Weathering' and Age Patterns of Allostatic Load among Blacks and Whites in the United States" *American Journal of Public Health* Vol.96(5): 826-833.

Heckman, J.J, H. Ichimura and P. Todd. (1998) "Matching as an Econometric Evaluation Estimator." *Review of Economic Studies*, Vol. 65(2), pp. 261-294.

Hill, T.D., C.E. Ross, and R.T. Angel (2005). "Neighborhood Disorder, Psychophysiological Distress, and Health," Journal of Health and Social Behavior, Vol. 46(2): 170-186.

Kaufman, P.R., J.M. MacDonald, S.M.Lutz, and D.M. Smallwood (1997). "Do the Poor Pay More for Food? Item Selection and Price Differences Affect Low-Income Household Food Costs". Agricultural Economic Report No. 759. Economic Research Service, U.S. Department of Agriculture.

Larson, N., M. Story, and M. Nelson. 2009. "Neighborhood environments: disparities in access to healthy foods in the U.S." *American Journal of Preventive Medicine* 36 (1): 74–81.

DRAFT- do not cite heck do not even read

Lee, H. 2012. “The Role of Local Food Availability in Explaining Obesity Risk Among Young School-Aged Children,” Social Science and Medicine 74 (2012): 1193-1203.

Leibtag, E. 2006. The Impact of Big-Box Stores on Retail Food prices and the Consumer Price Index. ERR-33. U.S. Department of Agriculture, Economic Research Service, Dec.

Massey, D.S. (2004). “Segregation and Stratification: A Biological Perspective,” Du Bois Review, Vol. 1(1): 7-25.

McEwan, B. (2000). “Allostasis and Allostatic Load: Implications for Neuropsychoparmacology.” Neuropsychopharmacology. 22: 108-124.

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Table 1: HEI 2005 v HEI 2010

Healthy Eating Index 2005 and 2010--components and standards for scoring[1]

2005				2010			
HEI-2005 Component	Maximum Points	Standard for Maximum Score	Standard for minimum score	HEI-2010 Component	Maximum Points	Standard for Maximum Score	Standard for minimum score
Total Fruit (includes 100% juice)	5	≥0.8 cup equiv. per 1,000 kcal	No Fruit	Total Fruit (includes 100% juice)	5	≥0.8 cup equiv. per 1,000 kcal	No Fruit
Whole Fruit(not juice)	5	≥0.4 cup equiv. per 1,000 kcal	No Whole Fruit	Whole Fruit(not juice)	5	≥0.4 cup equiv. per 1,000 kcal	No Whole Fruit
Total Vegetables	5	≥1.1 cup equiv. per 1,000 kcal	No Vegetables	Total Vegetables	5	≥1.1 cup equiv. per 1,000 kcal	No Vegetables
Dark Green and Orange Vegetables and Legumes[2]	5	≥0.4 cup equiv. per 1,000 kcal	No Dark Green or Orange Vegetables o	Greens and Beans[2]	5	≥ 0.2 cup equiv. / 1,000 kcal	No dark-green vegetables, beans, or peas
Total Grains	5	≥3.0 oz equiv. per 1,000 kcal	No Grains	Whole Grains	10	≥1.5 oz equiv. per 1,000 kcal	No Whole Grains
Whole Grains	5	≥1.5 oz equiv. per 1,000 kcal	No Whole Grains	Dairy[3]	10	≥ 1.3 cup equiv. / 1,000 kcal	No dairy
Milk[3]	10	≥1.3 cup equiv. per 1,000 kcal	No Meat or Beans	Total Protein Food[4]	5	≥ 2.5 ounce equiv. / 1,000 kcal	No protein foods
Meat and Beans	10	≥2.5 oz equiv. per 1,000 kcal	No Milk	Seafood and Plant[5]	5	≥ 0.8 ounce equiv. / 1,000 kcal	No seafood or plant proteins
Oils[4]	10	≥12 grams per 1,000 kcal	No Oil	Fatty Acids[6]	10	(PUFAs + MUFAs) / SFAs ≥ 2.5	(PUFAs + MUFAs) / SFAs ≤ 1.2
Saturated Fat	10	≤7% of energy5	≥15% of energy	Refined Grains	10	≤ 1.8 ounce equiv. / 1,000 kcal	≥ 4.3 ounce equiv. / 1,000 kcal
Sodium	10	≤0.7 gram per 1,000 kcal5	≥2.0 grams per 1,000 kcal	Sodium	10	≤ 1.1 gram / 1,000 kcal	≥ 2.0 grams / 1,000 kcal
Calories from Solid Fats, Alcoholic Beverages and Added Sugars	20	≤20% of energy	≥50% of energy	Empty Calories[7]	20	≤ 19% of energy	≥ 50% of energy

[1] Intakes between the minimum and maximum levels are scored proportionately, except for Saturated Fat and Sodium (see note 5).

[2] Legumes counted as vegetables only after Meat and Beans standard is met.

[3] Includes all milk products, such as fluid milk, yogurt, and cheese, and soy beverages.

[4] Includes nonhydrogenated vegetable oils and oils in fish, nuts, and seeds.

[5] Saturated Fat and Sodium get a score of 8 for the intake levels that reflect the 2005 Dietary Guidelines, <10% of calories from saturated fat and 1.1 grams of sodium/1,000 kcal, respectively.

[1] Intakes between the minimum and maximum standards are scored proportionately.

[2] Includes any beans and peas not counted as Total Protein Foods.

[3] Includes all milk products, such as fluid milk, yogurt, and cheese, and fortified soy beverages.

[4] Beans and peas are included here (and not with vegetables) when the Total Protein Foods standard is otherwise not met.

[5] Includes seafood, nuts, seeds, soy products (other than beverages) as well as beans and peas counted as Total Protein Foods.

[6] Ratio of poly- and monounsaturated fatty acids (PUFAs and MUFAs) to saturated fatty acids (SFAs).

[7] Calories from solid fats, alcohol, and added sugars; threshold for counting alcohol is > 13 grams/1,000 kcal.

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Table 2: Summary Statistics

Variable Name	Variable Definition	Mean *Standard error*		
		Total adult NHANES Sample (N=10,696)		Study sample—low income respondents in urban areas
Treatment variable				
Food desert	1 if individual lives in a low access neighborhood.			
Outcome variables				
HEI-2005	Healthy eating index 2005 score	54.938	*0.355*	
Fruit	Cups of fruit/1000kcal	0.525	*0.014*	
Whole fruit	Cups of whole fruit/1000kcal	0.348	*0.010*	
Grains	Oz of grains/1000kcals	3.165	*0.018*	
Whole grains	Oz of whole grains/1000kcals	0.371	*0.011*	
Vegetables	Cups of vegetables/1000kcals	0.857	*0.010*	
Dark green vegetables	Cups of dark green vegetables/1000ckals	0.139	*0.004*	
Saturated fat	Share of calories from saturated fat	11.220	*0.066*	
Sodium	Grams of sodium/1000kcals	1652.474	*8.177*	
Empty calories	Share of calories from added sugars, solid fats and alcohol	35.123	*0.253*	
FAFH/daily	Average number of meals away from home on recall days	0.897	*0.018*	
FAFH/weekly	Average Number of meals from food away from home/week	3.466	*0.089*	
Heavy smoker	1 if individual smokes a pack of cigarettes/day	0.098	*0.007*	
Drinks per day	Number of alcoholic beverages per day	0.469	*0.016*	
Binges per year	Number of times respondent had 4 or more drinks in the last year	11.231	*0.649*	
Illegal drug user	1 if respondent currently uses illegal drugs	0.110	*0.007*	
Matching/control variables				
PIR	Poverty to income ration	3.084	*0.052*	
Male	1 if male	0.480	*0.006*	
Age	Age in years	47.039	*0.357*	
Household size	Number of people in household	2.902	*0.036*	
Non-Hispanic white	1 if white, non-Hispanic	0.735	*0.020*	
Non-Hispanic black	1 if black, non-Hispanic	0.110	*0.012*	
Hispanic	1 if Hispanic	0.110	*0.012*	
Other	1 if any other race/ethnicity	0.045	*0.004*	
No high school/GED	1 if no high school degree or GED	0.173	*0.009*	
High school/GED	1 if only high school degree or GED	0.255	*0.009*	
Some college	1 if some college	0.306	*0.007*	
BS or more	1 if college degree or more	0.266	*0.014*	
Married	1 if married	0.572	*0.013*	
NHANES 2003-4	1 if surveyed in 2003-4	0.333	*0.022*	
NHANES 2005-6	1 if surveyed in 2005-6	0.322	*0.023*	
NHANES 2007-8	1 if surveyed in 2007-8	0.344	*0.020*	

Numbers in bold type indicate that the mean differences between respondents in low-access neighborhoods and respondents in non-low access neighborhoods are significantly different at the 10% level or above.

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Table 3 -- Summary of Allostatic Load measure

Variable	Threshold value	Full NHANES sample (N=7534)		Study sample—low income respondents in urban areas		
				Full study sample	Low access respondents	All other respondents
Blood pressure						
Systolic	>=140	122.470	*0.353*			
Diastolic	>=90	70.667	*0.283*			
Pulse	>=90	72.999	*0.267*			
Glycated hemoglobin	>=6.4%	5.531	0.021			
Albumin	<3.8 g/dL	4.262	0.008			
High-density lipoprotein	<=40 mg/dL	52.919	0.312			
C-reative protein	>3 mg/dL	0.411	0.014			
Total cholesterol	>= 240 mg/dL	198.549	0.727			
Total Allostatic load	Score ranges from 0 to 8	0.783	*0.023*			

Threshold levels are those used by Crimmins et al, 1999

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Table 4—Estimated treatment effect of living in a low-access neighborhood

VARIABLES	HEI-2005	Fruit	Whole fruit	Whole grains	Vegetables	Dark green vegetables	Saturated fat	Sodium	Empty calories
OLS Estimates									
standard error									
PSM Estimates									
standard error									
PSM/OLS Estimates									
standard error									
VARIABLES--cont'd									
OLS Estimates									
standard error									
PSM Estimates									
standard error									
PSM/OLS Estimates									
standard error									

Significant at *** p<0.01, ** p<0.05, * p<0.1

The linear regression estimates also control for the variables listed in table 2b—income, gender, age, race, education, marital status and survey round.

PSM estimates are derived from nearest neighbor treatment effects estimates, where individuals living in food deserts are matched to individuals outside of food deserts on the observable variables listed in table 2b.

PSM/OLS estimates are derived from a hybrid PSM/OLS regression procedure, where the outcome measures are regressed on food desert status and the control variables listed in table 2b. However, we limit the regression sample to respondents who were matched in the propensity score matching, and each observation is weighted by the number of times they were used in the matching.

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Table 5—Estimated treatment effect of living in a low access neighborhood after matching on Allostatic load

VARIABLES	HEI-2005	Fruit	Whole fruit	Grains	Whole grains	Vegetables	Dark green vegetables	Saturated fat	Sodium	Empty calories
OLS Estimates										
standard error										
PSM Estimates										
standard error										
PSM/OLS Estimates										
standard error										
VARIABLES										
OLS Estimates										
standard error										
PSM Estimates										
standard error										
PSM/OLS Estimates										
standard error										

Significant at *** p<0.01, ** p<0.05, * p<0.1

The linear regression estimates also control for the variables listed in table 2b—income, gender, age, race, education, marital status and survey round.

PSM estimates are derived from nearest neighbor treatment effects estimates, where individuals living in food deserts are matched to individuals outside of food deserts on the observable variables listed in table 2b.

PSM/OLS estimates are derived from a hybrid PSM/OLS regression procedure, where the outcome measures are regressed on food desert status and the control variables listed in table 2b. However, we limit the regression sample to respondents who were matched in the propensity score matching, and each observation is weighted by the number of times they were used in the matching.

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