Submitted Article

An Alternative to Developing Stores in Food Deserts: Can Changes in SNAP Benefits Make a Difference?

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Abstract In the search for policies to reduce the effects of limited food access, little consideration has been given to how economic incentives could be used to make it easier for low-income families to access existing healthy food retailers. Using county-level, administrative data on redemption of Supplemental Nutrition Assistance Program (SNAP) benefits by store type from May 2007 to May 2010, this paper investigates aggregate responses of SNAP participants to economic and policy changes. Results show that SNAP benefit increases, in general, are associated with a greater percentage of redemptions at superstores. However, other circumstances associated with the large increase in benefits enacted in April 2009 as a part of the stimulus bill reverse the positive effect. Estimates are stable across a number of specifications that also control for gas prices, store-type density, local unemployment and state policies. Results suggest that economic incentives deserve further consideration as an alternative to store development in food desert communities.

Key words: Food access, Supplemental Nutrition Assistance Program (SNAP), Food deserts, Food stamps.

JEL codes: I14, I38, Q18.

Introduction

High rates of obesity, diabetes, and other diet-related diseases in some low-income neighborhoods in the United States have raised concerns that these neighborhoods may lack access to healthy foods. Residents of such communities may be reliant on the offerings of nearby stores, which could mean they have relatively fewer choices for healthy foods, and face higher prices. However, if residents travel to stores with better selection or lower prices...
prices outside of their neighborhoods, they may incur greater transportation and time costs.

Several policy initiatives have been implemented to make healthy foods more accessible to such communities. Most of these efforts encourage the development of new or modified retailers in existing food desert communities; an alternative could provide assistance for people to access sources of healthy foods outside of their neighborhoods. Thus far, there has been little research or evaluation to guide which approach may be more effective in addressing access barriers.

The circumstances surrounding the increase in the Supplemental Nutrition Assistance Program (SNAP, formerly known as the Food Stamp Program) benefits through the American Recovery and Reinvestment Act (ARRA) provide a unique opportunity to understand how economic factors and an increase in the amount of money available to spend on food may affect food shopping behavior. The SNAP provides monthly benefits to low-income households that can be redeemed for groceries at authorized food retailers. These food retailers range from supermarkets and grocery stores, to convenience and specialty stores, to farmers’ markets. At the end of the U.S. 2011 Federal fiscal year, there were about 230,000 SNAP-authorized retailers (USDA 2012). In that same fiscal year (FY), SNAP served 44.7 million individuals, providing an average of $134 per person for groceries each month. Beginning in April 2009, the maximum SNAP benefit was increased by 13.6% through ARRA, or about $80 for a family of four. This increase in benefits may make it feasible for households who face access barriers to travel farther to stores (with presumably lower food prices), because the increase in benefits indirectly acts to offset travel costs.

A major objective of this study is to examine how an increase in SNAP benefit levels affects SNAP redemptions at supermarkets and supercenters (henceforth referred to as superstores). Controlling for the availability of stores by type, benefit increases are hypothesized to increase incentives for participants to shop at superstores, where prices tend to be lower, but which may be farther away or require greater travel costs. Because gas and food prices were also subject to significant variation over our study period, we control for their influence, as well as for local unemployment and state policy choices. The research has policy implications for understanding how an increase in resources through the SNAP program may change the shopping patterns of SNAP participants.

Our theoretical approach is an extension of the standard consumer demand analysis to accommodate travel costs for buying food, store choice, and income that includes an in-kind transfer. We use indifference curve analysis to illustrate a relevant choice problem for a representative SNAP household.

The percentage of SNAP redemptions at superstores is modeled as a function of maximum monthly benefits levels (deflated by food prices), store density by store type, and other economic and policy factors that may influence store shopping decisions and SNAP participation. The county is the unit of analysis, which is the smallest level of geography in our dataset. The analysis uses monthly county-level data on SNAP redemptions (in dollars) by store type from May 2007 to May 2010. County-fixed effects are used to control for any unobserved, time-invariant characteristics of counties that are correlated with our independent variables of interest.
Our results indicate that SNAP benefit increases are associated with a greater percentage of redemptions at superstores. However, other factors not associated with SNAP benefit changes tended to reduce superstore redemptions in the period after implementing the ARRA SNAP changes. Estimates are stable across a number of specifications that control for gas prices, store-type density, local unemployment and SNAP eligibility policy. According to our estimates, an $80 increase in the maximum SNAP benefit increases the percentage of benefits redeemed at superstores by 1.0 percentage point. When we subset our data based on the percentage of the population residing in food deserts, an increase in real benefit levels has a positive but smaller effect in counties with higher proportions of their populations in food deserts. Increases in gas prices tend to decrease supermarket redemptions in these counties as well.

Relevant Literature and Contribution

The U.S. Department of Agriculture (USDA) estimates that between 2-5% of households, or between 4-8% of individuals in the United States, face barriers in access to supermarkets and large grocery stores (2009). Ver Ploeg, Nulph, and Williams (2011) estimate that 13.6 million people in food deserts—low-income census tracts with a substantial number or share of residents who are far from a supermarket—have limited access to supermarkets. The majority of these almost 14 million people, 82%, reside in urban areas. The relationship between this lack of access and diet and health outcomes has become a research focus because obesity and diet-related health have become such pressing public health problems in the United States. A number of studies reviewed by Larson et al. (2009) have shown that limited access to healthy food options is associated with lower intake of some foods like fruits and vegetables and even to less proximate outcomes such as higher rates of obesity. But studies using methods that go beyond associations to show a causal link find no effect of access to supermarkets or other healthy food stores on dietary intake or body weight (Block et al. 2011; Boone-Heinonen et al. 2011; Cummins et al. 2005), or only find a small effect (Chen et al. 2010; Wrigley et al. 2003).

Even if the effect of food deserts on diet and health is not large, store access barriers may affect consumer shopping patterns—leading to consequences such as higher food costs and lower dietary variety. In general, in recent years there has been little research in the food desert literature on the economic factors that drive food shopping and how they may operate differently in different food environments. Much of what we know about these possible effects comes from studies of low-income and SNAP-participating populations. The Food and Nutrition Service (FNS) of the USDA has continuously tracked SNAP benefit redemption by store type. In FY2010, 83.5% of SNAP benefits were redeemed at supermarkets or supercenters where prices tend to be the lowest (USDA 2011). The remaining percentage was redeemed at smaller stores. Evidence from the 1996-1997 National Food Stamp Participant Survey (NFSPS) suggests that SNAP participants may not shop at the nearest supermarket. NFSPS respondents reported the modes of transportation used, the out-of-pocket costs incurred, and the amount of time taken to travel to stores where they usually shopped for food (Ohls et al.
Though these estimates refer to a representative population, not just one located in food deserts, they provide some insight into travel costs. Among program participants, the average distance to the nearest supermarket was 1.8 miles, but the average number of miles to the store most often used by participants and eligible nonparticipants was 4.9 miles.

This shopping behavior may be motivated by price considerations. Superstores, supercenters and other nontraditional food outlets (such as dollar stores and warehouse club stores) have been found to offer lower prices than traditional supermarkets and grocery stores (Leibtag 2006), and have been credited with lowering grocery prices in general with greater store competition (Hausman and Leibtag 2007). Broda et al. (2009) find that low- and middle-income households are more likely to purchase foods at supercenters than higher income households. This study also found that most, but not all, low-income consumers pay less for the same grocery items than higher income consumers—those with annual incomes between $8,000 to $30,000 tended to pay the least, while the poorest of the poor, those with incomes less than $8,000 paid 0.5-1.3% more for the same items.

Getting to these stores that offer the lower prices may have travel and time cost implications. USDA (2009) estimated the time spent traveling to stores for grocery shopping trips using American Time Use Survey data. Estimates show that shoppers who lived in low-income census tracts with low access to a supermarket or large grocery store spent an average of 19.5 minutes on one-way grocery shopping trips, which is larger than the U.S. average of 15.0 minutes.1 The NFPS respondents reported the modes of transportation and out-of-pocket costs used to travel to stores where they usually shopped for food, as well as how much time it took to travel to food stores, although this was for the general SNAP population, not specifically for those in food desert areas (Ohls et al. 1999). Close to 76% of participants and 85% of eligible nonparticipants reported using a car to shop.2 Average round-trip travel time to the most frequently used store was 23-24 minutes for participants and eligible nonparticipants. Among the 22% of participants who reported some transportation expenses, the average cost per shopping trip was $6.54.

Using the NFSPS survey data and data from the Louisiana Neighborhood Environment and Consumption Survey (LANECS), Rose et al. (2009) estimate travel costs for various modes of transportation for different areas in New Orleans. This exploratory exercise considered both out-of-pocket travel costs and time costs for the different travel options for grocery shopping.3 Estimates ranged from a high of $66.60 per month for a taxi, to $5.90 per month for driving one’s own car.4 The study also considered differences in time costs for New Orleans residents living in areas with poor access to supermarkets (defined as census tracts located more than 2 kilometers from a supermarket), compared with the time costs for those living in areas with good access (defined as census tracts within 2 kilometers of a supermarket). The average difference in travel cost

1The difference is statistically significant at a 90% confidence level.
2Among SNAP participants, 45% drove themselves and 31% received a ride from family or friends.
3The time cost estimates use the hourly minimum wage to value time. See table 5 in Rose et al. 2009, for details.
4Costs are to the nearest supermarket by mode of transport based on the approach by Feather 2003, and weighted using the distributional data on the mode of transportation.
between areas with poor access and areas with good access was $10.58 per
month; in other words, SNAP participants in poor-access areas of New
Orleans had total travel costs (both time and out-of-pocket costs) that were
on average (across mode of transportation) almost $11 higher than those
in areas with good access.

**Conceptual Model**

In making their food shopping decisions, households trade off travel
costs and price differentials at different types of stores. Transportation
costs directly reduce the income available for other expenditures, but rela-
tive access to different types of food stores also influences the nominal
prices paid for food. The availability of in-kind food benefits through the
SNAP program further complicates decisions.

A simple model of consumer behavior can be used to predict how
access to food stores affects the household’s budget constraint and shop-
ping destination decisions. Figure 1 illustrates a choice between food and
nonfood items and a choice between two stores—a convenience store with
small travel costs, and a superstore with lower prices for food, but signifi-
cant travel costs. We assume no travel costs for purchasing the nonfood
commodity. As illustrated in panel 1a, if no food is purchased, the
amount $I$ of the nonfood commodity can be purchased. If all available
income is spent on food, the amount $B$ can be purchased from the super-
store or $J$ from the convenience store. Purchasing food requires the house-
hold to incur travel costs. On the horizontal axis, the amount $HI$ is the
travel cost of reaching the nearest convenience store (normalized by the
price of the nonfood item), and $FI$ is the cost of reaching the nearest super-
store. If any food is purchased, the maximum amount of the nonfood
commodity that can be obtained is reduced by the travel costs for buying
food.

Without SNAP participation, the budget constraint $JH$ in panel 1a
shows the combination of food and nonfood commodities that can be
obtained when all food is bought at a convenience store. Likewise, the
budget line $BF$ shows the combinations possible at a superstore. The boun-
dary of these budget lines results in a non-convex budget set ($BKHI$).
Participation in SNAP substantially complicates the budget set due to the
in-kind nature of the benefit.

Introduction of the in-kind SNAP benefit does not affect travel costs or
the maximum amount of nonfood that can be purchased, but it does shift
up the budget line by the amount of food that can be purchased with the
SNAP allotment—which varies depending on the type of food retailer
chosen. As illustrated in panel 1b, the SNAP allotment obtains an amount
of food equal to the line segment $FM$, sacrificing nonfood purchases in the
amount of the travel costs, $FI$. Because food prices are higher in conven-
ience stores, less food can be obtained with the SNAP allotment, $HA$, but
less travel costs are incurred, $HI$. Differing food prices also account for the
difference in slopes of the store budget lines. Thus, when the in-kind
SNAP allotment is fully taken into account, the resulting combined
budget set ($GMNAHI$) can have several kinks.

Given this budget set, panel 2a shows a dual choice problem for a repre-
sentative SNAP household that involves not only the allocation of income
(net travel costs) between food and nonfood, but also the selection of the food store shopping location. Store choice is defined based on the segment of the budget constraint where utility is maximized. In panel 2a, utility is optimized at level \( L'' \) at the kink point \( A \). The SNAP benefit is used at a convenience store, travel costs of \( H_I \) are incurred, and only the SNAP allotment is used to purchase food.

An increase in SNAP benefits shifts the budget set. Due to store price differentials, an increase in SNAP benefits will generate a larger shift in the budget line for the superstore as opposed to a convenience store, thereby encouraging a change in shopping destination. This is illustrated in panel 2b where, without any change in cash income or prices, the benefit increase generates a shift from \( A \) to \( A' \).

To isolate the importance of a change in travel costs, panel 3 illustrates the case where a reduction in travel costs to superstores from amounts \( F \) to \( F' \) would also induce the representative SNAP household to shift to the superstore budget segment and allocate income (net travel costs) at point \( V \), with a higher utility level and a higher level of food purchasing.

**Figure 1** Conceptual Model of Store Choice
This analysis can be generalized to the travel cost model frequently used in recreational and transportation demand analysis (Feather 2003). In that approach, a household chooses which store to visit based on relative travel costs and the conditional indirect utility functions for the competing stores. In most applications, multinomial logit models are used to estimate the utility parameters. Because of data limitations, we take a simpler approach focusing explicitly on the choice to shop at superstores.5

**Data Sources**

Data for SNAP redemptions come from the USDA Food and Nutrition Service (FNS). This dataset provides county-level redemptions (in U.S. dollars) by store type for each month from May 2007 to May 2010. The data also include each county’s total SNAP redemptions (in dollars) and the number of redeeming retailer types. For protection of confidentiality, FNS redacted county-level SNAP redemption data for any store type with less than four authorized stores in a county.

FNS assigns one of 17 store types to retailers that are authorized to redeem benefits. Our analysis focuses on three major store types: supermarkets, combination stores, and convenience stores. These stores are the most commonly-occurring store types. The FNS defines the supermarket category to include establishments commonly known as supermarkets, food stores, grocery stores, and food warehouses that offer an extensive variety of grocery and other store merchandise where customers normally make large volume purchases. These stores typically have ten or more checkout lanes and are equipped with registers, bar code scanners, and conveyor belts.6 The FNS supercenter category includes very large supermarkets, “big box” stores, superstores and food warehouses primarily engaged in the retail sale of a wide variety of grocery and other store merchandise; this category includes stores that are large food/drug combination stores and mass merchandisers under a single roof, and membership retail/wholesale hybrids offering a limited variety of products in a warehouse-type environment (e.g., Walmart, Super Kmart, Target, Meijer, Fred Meyer, Sam’s, Costco, BJ’s). For our analysis, we combine the FNS supermarket and supercenter categories into a single superstore category (SS) to consolidate those establishments most likely to have a wide variety of food at low prices, including a wide variety of fruits, vegetables, whole grains, and other foods that are often under-consumed. We also use the FNS combination store (CO) and convenience store (CS) categories. The CO category encompasses general merchandise stores that also sell a variety of food products; stores such as independent drug stores, dollar stores and general stores that often offer low food prices but a more restricted variety of products. Convenience stores (CS) offer a limited line of convenience items, are typically open long hours, and offer a variety of canned goods, dairy products, pre-packaged meats, and other grocery items in limited amounts. They also usually sell a large variety of products ineligible for SNAP purchases such as hot coffee, alcohol, or tobacco

5In addition to having restricted data on SNAP redemptions, we lack the information needed to model other store attributes (e.g., food quality, variety or specific food and other item offerings), which are likely to affect store choice decisions.

6FNS includes three other categories for grocery stores: “large,” “medium,” and “small.” Stores classified as such were too infrequent to allow for inclusion in our dataset.
products. Some CS and CO may sell fruits, vegetables and whole grains, but the variety is often more limited than at SS and may be sold at higher prices. In FY 2010, 83.5% of SNAP benefits were redeemed in SS, 4.3% in CO, and 4.2% in CS (USDA 2011).

For our analysis sample, we select counties with non-missing data for the entire 37-month period. This initial sample consists of 533 counties (henceforth referred to as the “full sample”). Included counties are concentrated in the Pacific region, particularly California, as well as the Middle Atlantic, and parts of East North Central and South Atlantic regions. The 533 counties are located across 45 states, and 465 are located within a Metropolitan Statistical Area (MSA), 62 within a Micropolitan Statistical Area, and the remaining six are outside either Metro- or Micropolitan areas. Over the study period, there was a steady increase in the numbers of CS and CO stores authorized in these 533 counties, as illustrated in figure 2. Smaller increases in the number of supercenters account for the slight increase in the aggregated SS category.

The dependent variable of interest is the percentage of SNAP redemptions at superstores (SS). We compute this monthly measure by first summing each county’s redemptions at stores categorized by FNS as supermarkets or supercenters, and then dividing this sum by the county’s total SNAP redemptions. We multiply this quotient by 100 to obtain a percentage.

To control for food and gas price inflation, we utilize the Bureau of Labor Statistics’ metropolitan area and regional CPI data for food-at-home and gasoline (all types) prices, respectively. We assigned monthly CPIs based on the county’s MSA. If CPI data were missing for a particular MSA, we assigned a regional CPI based on the county’s Census division.

Figure 2 Number of SNAP Authorized Stores, Full Sample
and population size class. All CPI data were rescaled to a common base period (April 2009).

The SNAP maximum benefits vary according to household size and are uniform across states in the continental United States. The maximum benefit is adjusted annually for inflation based on the cost of the Thrifty Food Plan for a family of four, so we use the maximum benefit for a four-person household as a proxy for the benefit structure. This parameter is a primary policy lever which is exogenous to behavioral effects associated with the changing composition of the SNAP caseload. Since food prices vary substantially across regions and over time, we deflate the maximum benefit by the county’s assigned monthly food-at-home CPI and then multiply this quotient by 100. This yields a measure of the purchasing power of participants’ benefits, and it facilitates comparison of benefits over time. For a particular county, the purchasing power of SNAP benefits will be higher during months for which the index value is smaller, and vice versa.

We construct three store density measures using each county’s land area (in square miles): the number of CO per square mile; the number of CS per square mile; and the number of SS per square mile. The number of redeeming retailers varies, though not substantially, on a month-to-month basis. We also construct a population density measure using the Census Bureau’s yearly county-level population estimates (in 1,000s). This measure generates yearly, rather than monthly, variation in population per square mile for each county.

To control for important county economic and policy differences that may affect the size and composition of the SNAP caseload, we include the monthly county unemployment rate and a monthly variable indicating whether the county is located in a State that has enacted a policy to loosen income and/or asset eligibility requirements. We obtain monthly estimates of the county unemployment rate from the Bureau of Labor Statistics (BLS) Local Area Unemployment database. For the policy data, we created a dummy variable coded to indicate the months in which the eligibility expansion policy was in effect.

Finally, we explore the effect of benefit increases on redemptions at SS, specifically in areas where access to such stores is more limited. If benefit increases encourage redemptions at SS, the effect will depend on relative travel costs and store density within the local food environment. Ideally, we would use data on how many people in the county experienced food

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7The four Census divisions are Northeast, Midwest, South, and West. Population size classes are defined as follows: “A” if population exceeds 1.5 million; “B/C” if between 50,000 and 1.5 million; and “D” if under 50,000. Regional imputations were used for 431 of the 533 counties.
8Since 1977, the maximum benefit level in the continental United States has been tied to the cost of USDA’s Thrifty Food Plan (TFP) (USDA 2007). The TFP is a market basket of foods which, if prepared and consumed at home, would provide a complete, nutritious diet at minimal cost. The USDA updates the cost of the TFP monthly and the SNAP benefit is adjusted each October based on the TFP cost in the previous June. The maximum benefit for a four person household is based on the TFP cost for a family with two adults (19-50) and two children (6-8 and 9-11). Maximum benefits for households of other sizes are set based on fixed, economies-of-scale adjustments to the four person household maximum benefit. The benefit standard is higher in Alaska and Hawaii.
9County land area is based on the 2000 Census data.
10The policy option, officially known as “broad-based categorical eligibility” allows states to eliminate or modify federal asset limits, increase the income cutoff to 200% of the federal poverty level, and confer eligibility on clients who are provided with a minimal service, such as an informational brochure. Data on months of policy implementation by state are from Trippe and Gillooy (2010).
access barriers and their location within the county, but such data are not available. Instead, we use information on the proportion of a county’s population residing within a food desert. We utilize tract-level food desert data from ERS’ Food Desert Locator. The Locator defines low-income census tracts as food deserts if a substantial number or share of residents live far from supermarkets or large grocery stores.11 Tracts where more than 20% of people have incomes below federal poverty levels, or where the tract’s median income is at or below 80% of the larger area’s median income are designated as low-income tracts. Low-income urban census tracts are designated as food deserts if at least 33% of the tract population, or 500 people, are more than 1 mile from a supermarket or large grocery store; in low-income rural census tracts, a 10-mile designation is used.

Just over 6,500 census tracts are designated as food deserts in the US. These data contain information regarding the number of individuals living in food desert census tracts. We use this along with the county population estimate to calculate the proportion of the county population residing in food desert census tracts.12 The lower and upper terciles of this distribution are used to subset the counties into those with lower and higher food access problems.

Table 1 shows summary statistics for the key variables used in our analysis for each sample. The share of the county population residing in food deserts was 18.1 in the high food desert sample, compared to 1.7 in the low food desert counties. As expected, store densities are more than double for counties in the low food desert compared to the high food desert data sample. The SS density is larger by a factor of three. Similarly, the average population density in the low food desert subsample is more than triple that of the high food desert counties. Yet redemptions at SS, averaging 87.2% for the full data sample, were similar for the high and low food desert subsamples: 87.4% and 86.4%, respectively.13 Also notable is the fact that the maximum benefit (deflated by the food CPI and averaged over the sample) is slightly smaller for the high food desert subsample ($603) than for the low food desert ($609), which may indicate higher food CPI values (and higher food price inflation) for these counties.

**Empirical Model**

A primary purpose of our analysis is to examine how an increase in SNAP benefits affects redemptions at different store types. We hypothesize that the increase in benefits increases incentives for participants to shop at superstores, where prices tend to be lower, but may require greater travel costs. Additionally, we explore how shopping behaviors differ in counties with greater or lesser food access barriers.

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11The Food Desert Locator uses a 2006 list of supermarkets and large grocery stores, as well as data from the 2000 Census of the Population. See the documentation section of the Food Desert Locator for more details at: http://www.ers.usda.gov/data/fooddesert/documentation.html.

12We use county-level measures of food access because the SNAP redemptions data are only available at the county-level. However, these county measures are likely to mask significant variation in food access within a county, and thus, are weak measures of food access limitations.

13This could reflect the fact that our sample is restricted to metropolitan counties with at least eight superstores. Yet, travel costs are still more likely to be more of a factor in the high food desert subsample since the lower density of people and stores suggests that a larger share of county population will be far from a supermarket.
Unobserved heterogeneity across counties potentially confounds estimates of the effect of a benefit increase, but the availability of a panel data set enables us to employ a fixed effect framework. Using county-specific fixed effects, we control for any unobserved, time-invariant characteristics of counties that may be correlated with our dependent variable. The key assumption is that the unobserved county-specific effects are time-invariant once we control for observables. Under this framework, we exploit variation within counties over time.

Our baseline specification (model 1) incorporates our key variables of interest, as well as measures of store availability:

$$ss_{jt} = \gamma_j + \alpha \times \text{maxben}_{jt} + \theta \times \text{ARRA} + \beta \times x_{jt} + d + \varepsilon_{jt},$$

where $ss_{jt}$ indicates the ratio of supermarket and supercenter redemptions to total redemptions in county $j$ at time $t$ (each month from May 2007 to May 2010); $\gamma_j$ represents the county-specific fixed effect; $\text{maxben}_{jt}$ is the maximum benefit deflated by county $j$’s food-at-home CPI at time $t$; ARRA is a dummy equal to one for periods from April 2009 onward; and $x_{jt}$ is a vector of county characteristics likely to be associated with superstore redemptions, including population density and store densities (numbers of SS, CO, and CS per square mile); $d$ is a time trend; and $\varepsilon_{jt}$ is an i.i.d. error term by assumption.\(^{14}\)

The coefficients of interest are $\alpha$ and the $\beta$’s. We expect that $\alpha > 0$, that is, a higher maximum benefit is associated with an increase in the

\(^{14}\)Since the errors are likely to be serially correlated, all of our specifications cluster at the county level to obtain robust estimates of the standard errors.

### Table 1 Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th></th>
<th>High Food Desert</th>
<th></th>
<th>Low Food Desert</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Err.</td>
<td>Mean</td>
<td>Std. Err.</td>
<td>Mean</td>
<td>Std. Err.</td>
</tr>
<tr>
<td>Percent of population in food desert</td>
<td>9.307 0.364</td>
<td>18.459 0.584</td>
<td>1.711 0.124</td>
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<td>Percent SS redemptions</td>
<td>87.234 0.310</td>
<td>87.438 0.420</td>
<td>86.437 0.699</td>
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<td></td>
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<tr>
<td>Maximum benefit (deflated)</td>
<td>605.478 1.153</td>
<td>603.541 0.110</td>
<td>609.252 3.456</td>
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<tr>
<td>ARRA benefit boost in effect</td>
<td>0.378 0.000</td>
<td>0.378 0.000</td>
<td>0.378 0.000</td>
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<tr>
<td>Combination (CO) stores per square mile(^a)</td>
<td>0.114 0.020</td>
<td>0.073 0.007</td>
<td>0.194 0.059</td>
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<td></td>
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</tr>
<tr>
<td>Convenience (CS) stores per square mile(^a)</td>
<td>0.187 0.024</td>
<td>0.147 0.020</td>
<td>0.299 0.066</td>
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<tr>
<td>Superstores (SS) per square mile(^a)</td>
<td>0.116 0.018</td>
<td>0.066 0.007</td>
<td>0.208 0.053</td>
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<tr>
<td>Population per square mile (000s)</td>
<td>1.124 0.178</td>
<td>0.575 0.062</td>
<td>2.144 0.521</td>
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<td>Gasoline CPI</td>
<td>137.416 0.564</td>
<td>137.518 0.101</td>
<td>137.326 0.126</td>
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<td>Expanded eligibility in effect</td>
<td>0.319 0.018</td>
<td>0.338 0.032</td>
<td>0.326 0.030</td>
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<td>Unemployment rate</td>
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<td>7.770 0.178</td>
<td>6.919 0.127</td>
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<td>Number of Counties</td>
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<td>177</td>
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</table>

\(^a\)Arithmetic averages are presented here for variables later analyzed in logarithmic form.
percentage of SS redemptions. With respect to the \( \beta \)'s, we expect negative coefficients for the CO and CS densities, since their availability tends to reduce the likelihood of visiting superstores, and thus the percentage of superstore redemptions. Coefficients on SS densities are expected to be positive as the greater availability of such stores is likely associated with greater proximity, lower travel costs and increased redemptions. We expect the effect of the ARRA increase in SNAP benefits to be captured by \( \alpha \), but include an ARRA dummy variable to capture other changes in the post-ARRA economic and policy environment.

Because gas prices are also likely to affect travel costs, and therefore the decision of whether or not to travel to a SS, the next specification (model 2) includes county \( j \)'s regional gas CPI:

\[
ss_{jt} = \gamma_j + \alpha \times \text{maxben}_{jt} + \beta \times x_{jt} + \theta \times \text{ARRA} + d + \pi \times \text{gasprice}_{jt} + \epsilon_{jt}.
\]

Though our simple theoretical analysis suggests a negative sign for \( \pi \), previous literature cites other factors that make the sign ambiguous. Research from Gicheva et al. (2010) and Ma et al. (2011) shows that higher gas prices may also lead to shifts in less food away from home and more grocery shopping in general, not all of it at the lowest cost stores such as SS.

To control for county-level differences that are not time-invariant, our final specification (model 3) incorporates policy and economic variables:

\[
ss_{jt} = \gamma_j + \alpha \times \text{maxben}_{jt} + \beta \times x_{jt} + \theta \times \text{ARRA} + d + \pi \times \text{gasprice}_{jt} + \rho \times \text{eligibility}_{jt} + \varphi \times \text{unemployment}_{jt} + \epsilon_{jt},
\]

where \( \text{eligibility}_{jt} \) is a dummy variable indicating whether county \( j \) is located in a state that has adopted a policy to expand SNAP eligibility in month \( t \), and \( \text{unemployment}_{jt} \) is the unemployment rate in county \( j \) in month \( t \). Expectations for the signs of these variables are also ambiguous. Previous studies show that the expanded eligibility policy is associated with increased participation levels, especially for higher-income households (Klerman and Danielson 2011 and Wilde 2012). Such households may be more accustomed to shopping at SS, but, because of their higher incomes, will probably receive smaller monthly benefits which they might choose to spend on purchases at convenient stores. As for the local unemployment rate, a higher rate would imply more jobless individuals, some with time available for comparison shopping and travel to more affordable, distant stores. On the other hand, lower incomes associated with unemployment might place monetary constraints on travel by some households.

### Results

Table 2 includes the parameter estimates from the three specifications for the full sample counties and the high and low food desert subsamples. In general the results are significant and the signs are as expected. In all specifications, an additional dollar in the real (deflated) maximum SNAP benefit increases the amount of benefits redeemed at SS by about 0.01%. The parameter estimates associated with the ARRA dummy variable are
### Table 2: Parameter Estimates from Models of SNAP Superstore Redemptions

<table>
<thead>
<tr>
<th>Model 1 variables</th>
<th>All Available Counties</th>
<th>Higher Food Desert Counties</th>
<th>Lower Food Desert Counties</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum SNAP benefit (deflated)</td>
<td>0.013***</td>
<td>(0.002)</td>
<td>0.016 ***</td>
</tr>
<tr>
<td>ARRA benefit boost in effect</td>
<td>-1.862***</td>
<td>(0.133)</td>
<td>-2.104 ***</td>
</tr>
<tr>
<td>InfCombination (CO) stores/square mile</td>
<td>-0.841***</td>
<td>(0.292)</td>
<td>-1.068 ***</td>
</tr>
<tr>
<td>InfConvenience (CS) stores/square mile</td>
<td>-1.450***</td>
<td>(0.300)</td>
<td>-1.949 ***</td>
</tr>
<tr>
<td>InfSuperstores (SS)/square mile</td>
<td>9.304***</td>
<td>(3.497)</td>
<td>4.388 ***</td>
</tr>
<tr>
<td>Population per square mile (000s)</td>
<td>6.672*</td>
<td>(3.508)</td>
<td>-14.358 ***</td>
</tr>
<tr>
<td>Constant</td>
<td>94.109***</td>
<td>(11.806)</td>
<td>92.881 ***</td>
</tr>
<tr>
<td>Time trend</td>
<td>-0.023***</td>
<td>(0.006)</td>
<td>-0.005</td>
</tr>
<tr>
<td>Observations</td>
<td>19,721</td>
<td>6,586</td>
<td>6,549</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.213</td>
<td>0.273</td>
<td>0.252</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model 2 variables</th>
<th>All Available Counties</th>
<th>Higher Food Desert Counties</th>
<th>Lower Food Desert Counties</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum SNAP benefit (deflated)</td>
<td>0.011***</td>
<td>(0.003)</td>
<td>0.012***</td>
</tr>
<tr>
<td>ARRA benefit boost in effect</td>
<td>-1.674***</td>
<td>(0.224)</td>
<td>-1.700 ***</td>
</tr>
<tr>
<td>InfCombination (CO) stores/square mile</td>
<td>-0.850***</td>
<td>(0.293)</td>
<td>-1.084***</td>
</tr>
<tr>
<td>InfConvenience (CS) stores/square mile</td>
<td>-1.451***</td>
<td>(0.300)</td>
<td>-1.983***</td>
</tr>
<tr>
<td>InfSuperstores (SS)/square mile</td>
<td>9.028***</td>
<td>(3.497)</td>
<td>4.368***</td>
</tr>
<tr>
<td>Population per square mile (000s)</td>
<td>6.678*</td>
<td>(3.351)</td>
<td>-14.236 ***</td>
</tr>
<tr>
<td>Gasoline CPI</td>
<td>-0.001</td>
<td>(0.001)</td>
<td>-0.003***</td>
</tr>
<tr>
<td>Constant</td>
<td>95.334***</td>
<td>0.000</td>
<td>95.260***</td>
</tr>
<tr>
<td>Time trend</td>
<td>-0.021***</td>
<td>(0.006)</td>
<td>-0.0049</td>
</tr>
<tr>
<td>Observations</td>
<td>19,721</td>
<td>6,586</td>
<td>6,549</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.214</td>
<td>0.275</td>
<td>0.252</td>
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Continued
### Table 2 Continued

<table>
<thead>
<tr>
<th>Model 3 variables</th>
<th>All Available Counties</th>
<th>Higher Food Desert Counties</th>
<th>Lower Food Desert Counties</th>
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</thead>
<tbody>
<tr>
<td>Maximum SNAP benefit (deflated)</td>
<td>0.012***</td>
<td>(0.003)</td>
<td>0.012***</td>
</tr>
<tr>
<td>ARRA benefit boost in effect</td>
<td>−1.788***</td>
<td>(0.232)</td>
<td>−1.776***</td>
</tr>
<tr>
<td>InfCombination (CO) stores/square mile</td>
<td>−0.813***</td>
<td>(0.297)</td>
<td>−1.073***</td>
</tr>
<tr>
<td>InfConvenience (CS) stores/square mile</td>
<td>−1.470***</td>
<td>(0.303)</td>
<td>−2.088***</td>
</tr>
<tr>
<td>InfSuperstores (SS)/square mile</td>
<td>9.103***</td>
<td>(3.490)</td>
<td>4.362***</td>
</tr>
<tr>
<td>Population per square mile (000s)</td>
<td>6.692*</td>
<td>(3.539)</td>
<td>−13.682***</td>
</tr>
<tr>
<td>Gasoline CPI</td>
<td>−0.001</td>
<td>(0.001)</td>
<td>−0.001</td>
</tr>
<tr>
<td>Expanded eligibility policy in place</td>
<td>0.336*</td>
<td>(0.179)</td>
<td>0.085</td>
</tr>
<tr>
<td>County unemployment rate</td>
<td>0.042</td>
<td>(0.027)</td>
<td>0.100***</td>
</tr>
<tr>
<td>Constant</td>
<td>94.962***</td>
<td>(12.009)</td>
<td>94.197***</td>
</tr>
<tr>
<td>Time trend</td>
<td>−0.032***</td>
<td>(0.007)</td>
<td>−0.020***</td>
</tr>
<tr>
<td>Observations</td>
<td>19721</td>
<td></td>
<td>6,586</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.216</td>
<td></td>
<td>0.282</td>
</tr>
</tbody>
</table>

An Alternative to Developing Stores in Food Deserts
large by comparison, indicating a drop in superstore redemptions of nearly 2 percentage points. This effect is maintained even after controlling for county policy and economic factors (model 3).

The effect of additional CS stores per square mile is as expected; a 1% increase in the density of such stores is associated with a reduced percentage of redemptions at SS between 1.4-2.5%, with the high food desert sub-sample having the larger estimated effects. The situation is less clear for the CO stores. In the low food desert subset, where CO stores are less densely located than SS, CO store density does not have a statistically significant effect. In the high food desert subset, however, a 1% increase in the number of CO stores per square mile is associated with a 1.1% reduction in the percentage of SS redemptions; an effect roughly half the size of a 1% increase in CS density.

Given that high superstore density is associated with greater accessibility, it is not surprising that we find positive effects of increased SS density. Estimated coefficients range from 4.4 in the high food desert to 17.9 in the low food desert subset. In high food desert (low SS density) counties, a 1% increase in SS density would be associated with a 4.4% boost in the percentage of redemptions at SS. The estimated effect is more than three times larger in the low food desert subset where travel costs are easier to overcome.

Our estimates for the effects of changing gas prices mirror the mixed results found in previously discussed empirical literature. Gas price changes, as measured by the assigned gas CPI indices, have a statistically significant effect on the dependent variable only in high food desert subset of model 2, where a 1 unit increase in the gas price index is associated with a 0.003 percentage point decrease in the proportion of supermarket redemptions. Gas prices do not appear to affect SS redemptions in the low food desert counties.

Our results do not appreciably change with the inclusion of the eligibility and the unemployment variables. Both of these factors are positively associated with the dependent variable, but the effect appears to be strong only in the case of the unemployment variable in high desert counties, where a 1 unit increase in a county’s unemployment rate is associated with a 0.1 percentage increase in the proportion of redemptions at SS (model 3).

Somewhat unexpectedly, population density has a divergent relationship to the share of redemptions at SS. In low food desert counties, higher population densities are associated with a larger proportion of redemptions at SS. However, the opposite is true in high food desert counties where an additional 1,000 persons per square mile reduces superstore redemptions by 13.7 percentage points (model 3). We are not entirely sure of the source of this difference; it could be associated with a higher

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15In 2009 an average of 37,319 SS were authorized by SNAP in the entire United States. This translates into an average of 1.1 SS per 100 square miles. For our sample of 533 counties, overall superstore density (i.e., total number of superstores divided by total land area of all counties in the sample) is 4.0 SS per 100 square miles. For the high and low food desert subsets, it is 2.3 and 6.6 SS per 100 square miles, respectively.

16Alternative measures of transportation costs may better capture the effect we are trying to measure here.
After controlling for changes in store densities and other factors, there is a significant temporal decline in the proportion of redemptions at SS, which remains in the range of 0.02-0.03 percentage points per month. This trend is most evident in the low food desert subset.18

Table 3 translates the estimated effects from model 3 into rough impact estimates. The ARRA $80 real increase in the maximum benefit for a family of four is estimated to increase redemptions in SS by 0.96 percentage points in the full sample and the high food desert subsample.19 The same benefit increase has a slightly larger estimated impact in the lower food desert subsample, 1.12. In table 3, we compare this percentage effect with the effects of changes in the density of stores.

For the full sample, using estimates from model 3, SS density would have to increase by 10.5%, or from approximately 1 store every 22 square miles to 1 store every 20 square miles to generate a 0.96 increase in the dependent variable.20 For the higher food desert counties, the equivalent increase is estimated at 22%, or from 1 SS every 43 square miles to 1 every 35 miles. For low food desert counties, SS density would need to increase by 7.5%, or from 1 store per 15 square miles to 1 store per 14 square miles in order to match the 1.12 percentage point impact of the $80 benefit increase. Thus, achieving an equivalent increase in SS redemptions by SS development would require an additional 7-8 new SS stores in the high food desert area, as opposed to 4 new SS stores in low food desert areas.21

Policy Implications and Discussion

Residents of food desert communities may rely on the offerings of stores in their immediate community, which could mean they have fewer opportunities to purchase healthy foods such as fruits and vegetables, and face higher prices when they do. The potential diet and budget consequences for residents of food deserts have led to several policy initiatives

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17In an analysis of 2009 SNAP electronic benefit transfer (EBT) transactions, Castner and Henke (2010) present data showing that SNAP households belonging to non-white Hispanic and other minority racial groups, particularly Asians, tend to shop at more stores each month and redeem a smaller proportion of their benefits at superstores.

18Because we do not have SNAP redemption rates for every county in the United States, nor do we have a random sample of counties, we conducted sensitivity analysis for a subset of 206 counties, that is, those with a population of at least 300,000, for which inclusion in our data set was virtually complete. Separately estimated models using only these counties achieved results similar to those reported in this section.

19The 0.96 effect is obtained by multiplying the relevant parameter estimate, in this case 0.012, by the change in the real maximum benefit, 80.

20The percentage change in store density needed to match the added SS redemptions coming from an $80 increase in the SNAP maximum benefit (xtraSS) is calculated as follows: $xtraSS = b_j * d\ln(x_j)$, where $b_j$ is the estimated coefficient in model 3 for the logged store density measure $x_j$. Since $d\ln(x_j) = dx_j/\ln(x_j)$, we can solve as follows using the full sample data from tables 1 and 3: $dx_j/\ln(x_j) = 0.96/9.103 = 0.105$. We use this estimate with the geometric mean of the SS density measure (.045 SS per square mile for the full sample, 0.033 for the high desert subset, and 0.060 for the low desert subset) to convert the percentage change into impacts on SS density, and then take the inverse to obtain changes in square miles per store.

21For the additional number of SS needed, we use the change in SS density multiplied by the average land area per county (1,097 for the full sample, 1,474 for the high food desert subset, and 831 for the low food desert subset.)
<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>High Food Desert</th>
<th>Low Food Desert</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ARRA SNAP benefit increase</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$80 real increase in maximum benefit for a family of 4</td>
<td>0.96</td>
<td>0.96</td>
<td>1.12</td>
</tr>
<tr>
<td><strong>Superstore development</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Increase in number of superstores needed for equivalent percentage change in superstore redemptions</td>
<td>10.5</td>
<td>22.0</td>
<td>7.5</td>
</tr>
</tbody>
</table>

(Percentage increase in SNAP redemptions at superstores, average county)

(Percent increase in number of superstores per square mile, average county)
that aim to make healthy foods more accessible to such communities. For example, access to healthy food is one of five pillars of First Lady Michelle Obama’s Let’s Move campaign, which aims to reduce childhood obesity. Funding from existing programs of the U.S. Department of the Treasury, the U.S. Department of Health and Human Services, and the U.S. Department of Agriculture are being used to develop sources of healthy food in underserved neighborhoods as part of this initiative. The federal effort builds upon other state and local efforts to develop retail options in underserved areas in cities such as Philadelphia, New Orleans, and New York, as well as in areas of Pennsylvania and California.

These efforts share a common goal of bringing healthy food to underserved communities by encouraging the development of new retailers or modifying the offerings at existing retailers in food desert communities. An alternative approach that has received less policy consideration would be to provide assistance for people to access sources of healthy foods outside of their immediate neighborhoods.

Our results indicate that, in general, increases in SNAP maximum benefits positively impact redemptions at superstores in a range of diverse counties. Though we estimate the impact of the $80 maximum benefit increase to be smaller in those counties with higher proportions of their populations in food deserts, such a policy choice could possibly be more cost efficient than one supporting the development of an average of 7.5 new stores. However, when we combine the positive impacts of the $80 benefit increase with the estimated 2 percentage point negative impact associated with the ARRA dummy variable, redemptions at SS are estimated to be roughly 1 percentage point lower than they would have been in the absence of the ARRA SNAP changes. This raises one of several caveats that may limit the strength of our findings and conclusions.

Our conceptual framework considers only a single instance of store choice. By not taking into account the frequency of trips to different store types, we may miss an important aspect of how SNAP households reacted to the ARRA change. Using SNAP redemptions data, Castner and Henke (2010) found that in the six months after ARRA implementation, SNAP households made an average of 1.6 additional food store purchases per household per month compared to the six months before implementation. After ARRA, SNAP households shopped at more stores and, overall, the proportion of benefits redeemed at superstores declined by 1.2 percentage points. The increase in frequency of food shopping and in the number of stores accessed could have positive impacts on a household’s food situation that offset, to some extent, the negative impact of a decline in the percentage of SS redemptions. But the path through which these changes operate is not straightforward. Future research would benefit from joint consideration of relative expenditures at different store types, shopping frequencies and number of different stores accessed.

Our empirical approach that treats store density measures as fixed could be too simplistic. The number and types of SNAP-authorized stores

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23Our data only allow analysis of spending patterns from SNAP benefits. Since SNAP supplements the food budgets for most participants, it is possible that an increase in SNAP benefits may reduce the percentage of other income spent in superstores, though a reduction in the quantity of food purchased at superstores is not theoretically likely.
could respond to modifications in SNAP benefits and thus the store
density measures could change in a manner that is correlated with the
error term of our model. As noted in figure 2, SNAP store authorizations
increased in our sample of 533 counties over the study period, primarily
in the CO and CS categories. The pace of increase for these store types
was slightly greater after the SNAP ARRA changes took effect in April
2009. Our results might be strengthened by examining the extent of endo-
geney in store density.

The composition of the SNAP caseload could have changed greatly over
the study period as a result of the Great Recession, in ways that may be
correlated with increased redemptions at SS. If the recession translated
into a SNAP caseload that had slightly higher incomes or resources such
as vehicles, more of the caseload may have been able to access SS that are
farther away. We used county-level unemployment statistics and state-
level SNAP policy rule variation as possible controls for changes in case-
load characteristics and our results did not differ substantially. Future
work could explore other variables, such as vehicle ownership by SNAP
households, to better capture these changes.

Another potential limitation of our county-level analysis is that SNAP
participants can redeem benefits in neighboring counties. We do not have
data that would allow us to measure the extent to which this happens.
Our sample includes larger counties with at least eight superstores which
are scattered across the country. Because of this, we expect cross-county
redemptions to be less of a problem than it would be in a situation where
contiguous counties with smaller populations and store densities made up
the sample. Even so, the use of aggregated, county-level measures masks
significant variation in food store access factors within a county and thus
diminishes, to some extent, the strength of our estimates and comparisons
between high and low food desert areas. Disaggregated redemptions data
are needed to analyze differential behavioral responses for high and low
food desert areas.

To conclude, our research suggests that changes in SNAP benefits can
potentially favor the use of lower-cost, less accessible food shopping alter-
 natives by SNAP participants. This may be of importance in areas with
higher proportions of their populations living in food deserts. While prior
policy efforts to improve food store access have focused on supporting the
development of new stores, targeted incentives to raise benefits or reduce
travel costs could potentially be cost-effective alternatives. Given current
Federal budget realities, future expansions in SNAP benefits or wide-
spread Federal investments in food store development are unlikely. This
suggests the need for further comparative cost research on alternative poli-
cies. One cost-neutral possibility worth consideration would be to allow
SNAP participants to convert a portion of their benefits as “access dollars”
to fund transportation costs to more economical shopping venues.

References

Amanor-Boadu, V. 2009. In Search of a Theory of Shopping Value: The Case of
Food Establishments and Body Mass Index in the Framingham Heart Study


——. 2012. Building a Healthy America: A Profile of the Supplemental Nutrition Assistance Program.