Quantifying the Effects of Food Access and Prices on Food-at-home Demand

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Policy makers are increasingly looking to strategies that promote healthy eating, reduce obesity, and improve public health. Some argue that improving access to healthy foods, such as by eliminating the so-called food deserts, may have a meaningful impact on diet quality. Others have proposed that large targeted taxes, which focus on narrowly defined categories of foods and beverages with little to no nutritional value, may be an effective approach to improving population diet outcomes. With multiple and sometimes competing obesity policy options under consideration, policy makers are demanding more evidence from researchers to make informed policy decisions. Sound obesity policies are those more likely to reduce obesity and minimize the economic burden of such policies, as would be the case in using price disincentives to discourage unhealthy food consumption, especially on low-resource communities and lower-income households, whose children are also more likely to be at risk for overweight and obesity.

A number of studies have examined the association of food access (grocery stores and fast-food restaurants) with respondents' diet and weight status with mixed results. Although some do not find fast-food availability to have a statistically significant effect on obesity (Powell, 2009; Anderson and Matsa, 2011), others are able to detect a statistically significant, and sometimes sizable, effect of greater fast food availability on weight gain in certain populations (Chou et al., 2004; Dunn, 2010; Currie et al., 2010; Chen et al., 2012). The literature exploring the relationship between food store access and diet or weight outcomes has generated equally mixed findings (e.g., Boone-Heinonen et al., 2011; Lin et al., 2012; Harding and Lovenheim, 2014).

Almost all existing large-scale nutrition epidemiology studies on the food access–obesity relationship make the simplifying assumption that supermarkets provide healthier and more affordable food options, while convenience stores and fast-food restaurants offer unhealthy foods.

Under this assumption, measures of healthy food access are constructed based on food establishment counts within a geographic area (e.g. census tract). This dichotomous distinction between supermarkets and their smaller competitors ignores the reality that the selection and overall nutritional quality of food products often vary significantly across different supermarket chains and independent grocers. For example, Volpe, Okrent, and Leibtag (2012) found that the baskets of food purchased at supercenters (e.g., Walmart Supercenter and Super Target) have a lower degree of adherence to USDA dietary guidelines than those purchased at traditional supermarkets. Studies using food access measures based on store counts, while useful in predicting the dietary and health effects of adding a supermarket or eliminating a convenience store, cannot shed light on the potential effect of improving the nutritional profile of foods sold at existing supermarkets or smaller food stores.

The objective of this paper is twofold. First, we develop a new measure of healthy food access using GIS data on store locations and detailed household scanner data on retailer-specific food sales. Second, we incorporate the new measure in a utility-theoretic demand system model that includes *all* food-at-home purchases to examine the association between food demand and neighborhood food environment. Our measure of healthy food access is based on imputed HEI-2005 for all major food retailers and calculate food sales-weighted HEI for the neighborhood of each household in our scanner data. The HEI-2005 is a tool developed by USDA to evaluate diet quality based on conformance to the 2005 Dietary Guidelines for Americans (DGA) (Guenther et al., 2007). Although the HEI has been most often used to score the quality of respondent dietary intakes, Reedy et al. (2010) demonstrated the utility of HEI-2005 in evaluating the food environment by indexing the nutritional quality of U.S. aggregate food supply and foods offered at a fast-food restaurant. The HEI-2005 scoring system consists of 12 components, some of which the system rewards for increased consumption (e.g., whole fruits, whole grains), while others are penalized for higher intake (e.g., saturated fat, calories from solid fat, alcohol, and added sugar). USDA prepared the Food and Nutrient Database for Dietary Studies 3.0 (FNDDS) and the MyPyramid Equivalent Database (MPED) to be used jointly to assign the exact HEI-2005 score to approximately 7,000 foods in FNDDS. However, there is no publicly available cross-walk between the 400,000 food UPCs in scanner data and FNDDS that allows one to calculate the exact HEI score for all UPC items.

Volpe et al. (2012) proposed a regression-based approach to impute HEI scores for Homescan households. Their method regresses the HEI score of NHANES dietary recall respondents on daily intakes of 30 food-at-home categories, which are defined by Volpe et al. and mapped one for one to 30 food categories in Homescan. The coefficient estimates are then used to impute HEI scores for Homescan households using Homescan purchase data. Similar imputation strategies have been adopted in nutrient profiling research by nutrition epidemiologists (e.g. Arsenault et al. 2012). We use the Volpe et al. method to impute the HEI score for all major food retailers. Because most consumers shop at more than one retailer outlet, we use weight share, not gram weight, as covariates to circumvent the need for standardizing retailer sales into per capita/day basis.

MODEL

The demand model is the approximate Exact Affine Stone Index (EASI) demand system (Lewbel and Pendakur 2009). We follow Zhen et al. (2014) to account for censored demand and endogeneity as follows:

(1)
$$w_{hit}^{*}=\sum_{j=1}^{J}a_{ij}\ln p_{hjt}+\sum_{r=1}^{L}b_{ir}y_{ht}^{r}+\sum_{k=1}^{K}g_{ik}d_{hkt}+\sum_{l=2}^{N}v_{il}z_{hlt}+u_{hit},$$
$$h=1,...,H;\ i=1,...J-1;\ t=1,...,T;$$

where w_{hit}^{*} is the latent budget share of category i in period t for household h; J is the number of goods; the J th good is the composite numéraire good; H is the number of households; y_{ht} is real household income; L is the highest order of polynomial in y_{ht} to be determined empirically; p_{hjt} is price index of the j th good; K is the number of socio-demographic variables, d_{hkt}, including a constant term; z_{hlt} is a transformation of spatial lags of household h's neighborhood food healthfulness discussed below; N is the lag length to be determined empirically; a_{ij}, b_{ir}, g_{ik}, and v_{il} are parameters; and u_{hit} is the residual. The latent share w_{hit}^{*} is related to observed budget share w_{hit} according to $w_{hit}\equiv\max\{0,w_{hit}^{*}\}$, where w_{hit} is calculated as the category expenditure divided by quarterly household income. The y_{ht} term is the Stone price-deflated real income defined as $\ln x_{ht}-\sum_{j=1}^{J}w_{hjt}\ln p_{hjt}$, where x_{ht} is nominal quarterly household income. Included socio-demographic variables are household size and 11 binary indicators: three Census regions; presence of female household head; female household head below age 35; female household head with college degree; black, Asian, other race, or Hispanic household head; and children.

Previous studies have created Euclidean buffers of various sizes (e.g. 1, 3, 5 km) from the respondent's residence and used store counts in these buffers as measures of healthy food access (e.g. Boone-Heinonen et al. 2011). We depart from that approach by drawing concentric circles of different radii from the household's residential location. We measure healthfulness of foods sold in each annulus using retailer sales-weighted HEI. Denote the HEI scores for all annuli in ascending distance from h's residence in period t as c_{hmt} ($m = 1,2,...,M$), where M is a number large enough that the household is unlikely to shop beyond the associated annulus. We use Mitchell and Speaker's (1986) polynomial inverse lag (PIL) to specify a flexible spatial lag structure that places sufficient structure to allow us to estimate the spatial distribution empirically and to reduce chances for spurious results that may result from including unstructured spatial lags. The PIL has advantages over other commonly used lag structures such as the Almon (1965) lag. First, the researcher does not need to specify a priori the lag length or impose an end point restriction because the PIL has an infinite distributed lag structure. Second, the PIL is linear in the transformed lag variables. The transformed spatial PIL variable is constructed as $z_{hlt} = \sum_{m=1}^{M} \frac{c_{hmt}}{m^l}$, $l = 2,..., N$. The marginal effect of the untransformed lag on budget share is

(2) $$\frac{\partial w_{hit}}{\partial c_{hmt}} = \sum_{l=2}^{N} \frac{v_{il}}{m^l}, \; m = 1,..., M$$

To account for potential price endogeneity arising from consumer price search, we instrument p_{hjt} using the mean price of other households, excluding those within x km from h, in the same market and time period weighted by the inverse distance to h. We estimate the demand model (1) using Amemiya's generalized least squares (AGLS) estimator (Newey 1987) extended to a system of Tobit equations (Zhen et al. 2014).

DATA

Retailer location data are from annual files of business establishments from InfoUSA. Retailer-specific HEI scores imputed based on Homescan data for each quarter during 2004-2006 are linked to InfoUSA data to calculate sales-weighted HEI for each annulus around the residential location of the Homescan household.

We largely follow the categorization of foods in Volpe et al. (2012) with one modification: we reclassified their carbonated beverage and noncarbonated beverage categories into the categories of sugar-sweetened beverages (SSB) and non-SSB. This allows us to examine the effect of a SSB tax on demand for all food-at-home items and the overall HEI. We estimate the EASI demand model using data from the Homescan fresh foods panel in 52 Nielsen markets.[1] The fresh foods panel was a subset of the Homescan panel that reported purchases of foods with and without barcodes, while the larger Homescan panel only reported purchases of barcoded foods. This allows us to examine demand for several food categories (mostly fruits and vegetables) that positively contribute to HEI but include a lot of items without barcodes. The sample for demand estimation has 9,624 unique fresh foods panel households providing 83,580 quarterly observations. Of these households, 27%, 28%, and 45% participated in one, two, and all three years of the sample, respectively.

Table 1 provides some descriptive statistics by food category.

THE FOOD ENVIONMENT

RESULTS COMING SOON…

DEMAND ESTIMATION RESULTS

RESULTS COMING SOON…

CONCLUSION

NOT YET AVAILABLE

Table 1: Descriptive Statistics

Food categories	Unit value (cents/g) Low income	Unit value (cents/g) High income	Quantity (per capita g/day) Low income	Quantity (per capita g/day) High income
1. Whole fruit	0.218	0.248	87.1	93.5
2. Fruit juice	0.123	0.136	56.5	59.7
3. Dark green vegetables	0.311	0.339	6.2	7.7
4. Orange vegetables	0.209	0.233	8.2	8.6
5. Starchy vegetables	0.158	0.186	35.5	31.0
6. Other-nutrient dense vegetables	0.277	0.325	18.0	19.2
7. Other-mostly water vegetables	0.234	0.270	31.7	33.5
8. Legumes	0.141	0.162	3.8	3.4
9. Whole grains	0.477	0.507	21.5	22.3
10. Refined grains	0.218	0.250	93.4	82.7
11. Low fat dairy	0.159	0.172	113.8	118.7
12. Regular fat dairy	0.520	0.661	46.9	37.6
13. Low fat red meat	0.771	0.883	10.3	11.6
14. Regular fat red meat	0.602	0.718	49.5	43.5
15. Poultry	0.481	0.565	29.7	28.9
16. Fish	0.755	0.970	8.8	9.4
17. Nuts and seeds	0.630	0.708	9.5	10.6
18. Eggs	0.188	0.209	14.7	13.0
19. Oils	0.506	0.656	6.4	5.3
20. Solid fat	0.391	0.486	12.0	10.1
21. Sugar and sweeteners	0.162	0.196	16.2	11.1
22. SSB	0.083	0.095	198.2	167.6
23. Non-SSB	0.065	0.075	124.8	142.4
24. Water	0.054	0.052	77.1	102.0
25. Frozen commercially prepared sweet items	0.400	0.462	24.7	23.0
26. Other commercially prepared sweet items	0.504	0.567	66.8	65.4
27. Frozen commercially prepared non-sweet items	0.581	0.660	36.5	35.5
28. Canned commercially prepared non-sweet items	0.207	0.229	35.8	34.7
29. Packaged commercially prepared snacks	0.635	0.721	24.8	26.4
30. Other commercially prepared non-sweet items	0.624	0.740	32.3	27.6

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[1] About 85% of Homescan households resided in one of 52 Nielsen markets. The other 15% were from nine remaining areas of the contiguous United States.