AGRICULTURAL ECONOMICS

Agricultural Economics 49 (2018) 587–597

Does a nutritious diet cost more in food deserts?

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Received 7 October 2017; received in revised form 16 February 2018; accepted 5 April 2018

Abstract

Food deserts and their potential effects on diet and nutrition have received much attention from policymakers. While some research has found a correlation between food deserts and consumer outcomes, it is unclear whether food deserts truly affect consumer choices. In this article, we compare food prices in food deserts, defined as low-income, low-access census tracts, and nonfood deserts to observe whether and to what extent consumers face higher prices for a complete diet in food deserts. If a nutritionally complete diet costs significantly more in food deserts, resident consumers may be constrained from consuming healthier foods. We use store-level scanner data from a nationally representative sample and calculate a census-tract level Exact Price Index (EPI) based on a food basket defined by the Thrifty Food Plan (TFP). The EPI addresses potential biases from both product heterogeneity and variety availability. We find that the overall price impact of living in a food desert is small; low-access areas have only 3.5% higher EPI than high-access counterparts. However, consumers who are constrained to shop within their own census tracts face a much higher EPI than high-access counterparts (9.2%). The higher EPI primarily comes from lower variety availability in food deserts.

JEL classifications: D40, I3, L66, Q18, R32

Keywords: Food deserts; Food price; Nutritious diet; Price indices; Product variety

1. Introduction

Limited access to healthy food in the U.S. has been associated with poorer diet quality (Bodor et al., 2008; Michimi and Wimberly, 2010; Morland et al., 2002; Zenk et al., 2009), and a higher probability of obesity and other dietary-related health problems (Carroll-Scott et al., 2013; Larson et al., 2009). In addition, households with lower socioeconomic status are more likely to live in food deserts and purchase less healthful food (Allcott et al., 2017; Binkley and Golub, 2011; Handbury et al., 2016). In response, federal, state, and local initiatives have emerged to address the challenge of food deserts, including subsidizing large grocery retailers to move into underserved areas, improving food options in corner stores, and encouraging mobile grocery vendors. Multiple states have also enacted legislation aimed at increasing the number of healthy food retailers or have subsidized local stores to provide fresh fruits and vegetables.

Implicit in these interventions is the idea that food deserts, defined as geographic areas with low-income and low food access, are thought to have higher food prices and lower availability of healthy foods than nonfood deserts. These assumptions are based on case-study comparisons of food prices and availability that focus on a single community (e.g., Andreyeva et al., 2008; Block and Kouba, 2006; Chung and Meyers, 1999) or one or two store chains (e.g., Hatzenbuehler et al., 2012). Other studies compare prices of specific food items, such as fresh fruits and vegetables (e.g., Hayes, 2000; USDA, 2009). However, recent studies such as Handbury et al. (2016) document that prices of commonly available goods are actually not significantly different in food deserts versus nonfood deserts based on a large sample of stores and food items across the United States. In this article, we further include access to variety into the price index and compare the variety-adjusted price index between food deserts and nonfood deserts. We specifically compare food prices in food desert census tracts to those

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We gratefully acknowledge financial support through Cooperative Agreement No. 58-5000-1-0051 between the University of Illinois and the Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA). We would like to thank editor Awudu Abdulai, three anonymous referees, Jessie Handbury, Paula Dutko, Joseph Llobrera, Lisa House and Parke Wilde for their help and suggestions on this paper. The views expressed in this paper are of the authors and should not be attributed to those of the Economic Research Services, the USDA or the IRI.

 DOI: 10.1111/agec.12444

in census tracts of similar income but higher food access, and census tracts of similar access but higher income to differentiate the effect of access and income on price and availability.

We use weekly barcode level store sales data for a nationally representative geographic sample from Information Resources, Inc. (IRI) in 2012 and build a localized price index for each census tract to be able to relate it to the same geographic scale used to designate food deserts. We define an affordable and nutritious diet following the USDA Thrifty Food Plan (TFP), which is a minimum cost diet based on low-income households' purchasing behavior and nutritional guidelines.

We construct a localized TFP Exact Price Index (EPI) following the approach developed by Broda and Weinstein (2010) and Feenstra (1994) and applied by Handbury and Weinstein (2014) (see Feenstra, 2010 for a review of its use).[1] Our localized TFP EPI is composed of both a Conventional EPI (CEPI) that accounts for the prices of food available in the census tract and a Variety Adjustment (VA) term that addresses the problem that some foods are unavailable in some locations, causing variety bias. Assuming nested Constant Elasticity of Substitution (CES) preferences, the price index measures the minimum cost needed for consumers to achieve the same level of utility in a census tract. The VA uses both estimated elasticities of substitution and national expenditure shares of each barcode to capture the impact of variety on prices. We use barcode-level prices rather than average costs for broad food categories to ensure we are not comparing prices for different product qualities, called product heterogeneity. Handbury and Weinstein (2014) show that after controlling for product heterogeneity and variety availability across cities, contrary to previous findings, larger cities have lower food prices than smaller cities.

After constructing the price indices, we regress the CEPI, VA, and EPI against a low access indicator variable and a number of factors that influence demand including neighborhood socioeconomic variables and county fixed effects. We restrict our analysis to urban census tracts to avoid comparing food deserts across different definitions in urban and rural areas. The purpose of this regression analysis is to study how stores' prices differ across neighborhoods with observably equivalent demand. Research has demonstrated that stores in areas with a limited number of competitors possess greater market power and charge higher prices (Smith, 2004). Although the regression results from our study cannot be interpreted as causal, they provide evidence of the extent of pricing and variety differences by income levels and access to stores.

Our article makes several contributions to the literature on food deserts. First, we construct a theoretically founded price index that overcomes a large number of problems that have plagued spatial price index measurement, i.e., product heterogeneity and variety bias. Second, the variety-adjusted price index (EPI) combines and quantifies the monetary value of food price and food availability based on a unified framework. In doing so, we can evaluate the welfare impact of living in a food desert where high food prices and low food availability are two major concerns.

One reason for the concern about these price effects is the common assumption that healthy foods are more expensive and/or less available in food deserts. To rigorously address this issue, a theoretically sound price index that accounts for food availability is needed. So, we construct a theoretically founded price index at the census tract level and, through this, identify both whether a standard basket of food has a similar price in food deserts and nonfood deserts, and whether there are differences in the availability of foods. The former helps us identify whether a standard set of foods which, by definition, include "healthy foods" are more expensive and the latter helps us identify whether there are variety differences which are often associated with "healthy eating." Dietary diversity and variety are key elements of high quality diets (Kant et al., 1993; Lo et al., 2013; Ruel, 2003). Increasing the variety of foods across and within food groups is recommended in most dietary guidelines, both in the U.S. (HHS and USDA, 2015) and internationally (WHO, 2015). Diet quality depends on consumer choices, which are affected by the food prices, availability, and retail environment they face (Staudigel, 2012). Therefore, availability, variety, and prices are key issues for policymakers when deciding what to do about food deserts, if anything.

Our central findings are as follows. First, when the observable demand is equivalent, stores in low access census tracts charge slightly higher (0.9%) prices and have lower food availability (2.6%) than their high-access counterparts. Combined, the variety-adjusted price index is 3.5% higher in low-access areas, which may not be high enough to deter food deserts residents from consuming more healthy foods. Second, this 3.5% price difference found between low access and high access areas is driven by a lack of supermarkets. However, given the small price difference, supermarket entry may have limited effects on enabling a more affordable basket of a wide array of food products. Third, we find substantial heterogeneity in the price effect of being in a food desert. Consumers who are constrained to shop within their resident census tracts face significantly higher prices (9.2%) in low-access tracts than high-access counterparts and are therefore more negatively affected by living in a food desert.

2. Methods

We begin with the intuition behind the potential gains from variety illustrated in Fig. 1 (Feenstra, 2010). Suppose a consumer gains utility from the consumption of two goods available in local market c (q_{1c} and q_{2c}). If the consumer has access to both goods, then to achieve the level of utility, AD, the consumer would choose to consume at point C and only spend the amount of money denoted by EF. However, if q_{2c} is not

[1] Broda and Weinstein (2010) construct the annual nation-level EPI for all consumer goods including nonfood items such medicine, electronics, and appliances in the U.S. Handbury and Weinstein (2014) devise the city-level EPI for all food. In this article, we focus on a census-tract level EPI for all food.

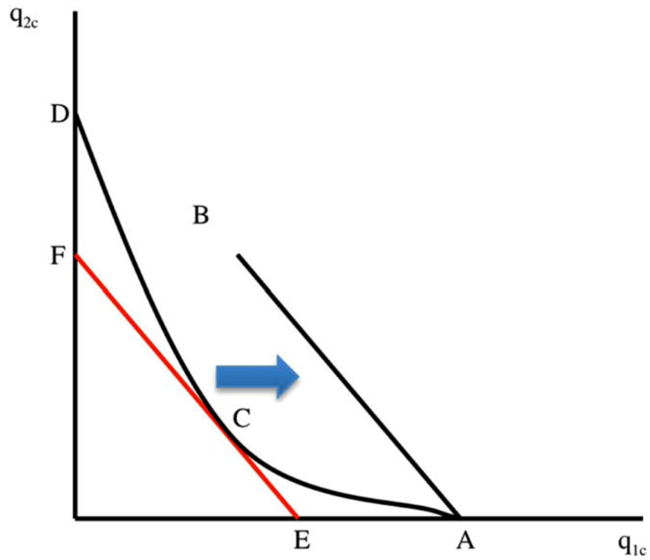

Fig. 1. Grains from variety. [Color figure can be viewed at wileyonlinelibrary.com]

available in the local market, to achieve the same utility level of AD, the consumer can only choose point A as the consumption bundle and needs to spend more money indicated by the minimum cost line AB. How much the cost will increase depends on the per-unit utility of the missing good and the substitutability of the available good compared to the missing one. The increase in cost needed to achieve the same level of utility when one does not have access to all varieties of goods formulates the gains from variety (Feenstra, 1994). The variety-adjusted price index (EPI) is the relative minimum cost to obtain a basket of food for consumers in a local market. The theoretical model is adapted from Broda and Weinstein (2010) and Handbury and Weinstein (2014) and is provided in Appendix A to explain how the expression of EPI is derived to capture the minimum cost to achieve the same level of utility across local markets.

There are two components of the EPI. One is the unadjusted price index, the CEPI. It measures the prices of foods that are available in the local market and is given by the weighted product of the price index of each food group. Specifically, the weight W_{gc} is the log-ideal CES Sato (1976) and Vartia (1976) weights that give more weight to *food groups* that are more important in the local market (a detailed definition of W_{gc} is provided in Appendix B). The CEPI for food group g in the local market c is given by

$$CEPI_{gc} = \prod_{u \in U_{gc}} \left(\frac{V_{uc}/Q_{uc}}{\sum_c V_{uc}/\sum_c Q_{uc}} \right)^{W_{uc}}, \tag{1}$$

where V_{uc} and Q_{uc} are local expenditure and quantity spent on Universal Product Code (UPC or barcode) u across all stores in the local market c, and U_{gc} is the set of all UPCs of food group g available in the local market. The variable W_{uc} are the Sato and Vartia weights for *UPCs* defined in Appendix B. The CEPI is a relative price, where the numerator is the price for a UPC in local market and the denominator is the national average price for a UPC.[2] The price index is weighted by the Sato-Vartia shares for each UPC in local market (W_{uc}), which captures the importance of each UPC locally.[3]

The other component of the EPI, the VA or a measure of variety availability is given by the weighted product of variety index of each food group multiplied by food group availability index $S_c^{\frac{1}{1-\sigma}}$. The weight for each food group (W_{gc}) is the same as in Eq. (1) and variety index of each food group is given by

$$VA_{gc} = \left(S_{gc}\right)^{\frac{1}{1-\sigma_g^a}} \prod_{b \in B_{gc}} \left(S_{bc}\right)^{\frac{W_{bc}}{1-\sigma_g^w}}. \tag{2}$$

Similarly, W_{bc} is the Sato and Vartia weight for brand-product b in the local market c defined in Appendix B and B_{gc} is the set of all brand-products belonging to food group g in the local market c. Food is split into three tiers within the nested framework. All food items (UPCs) are, first categorized into different brand-products, and second, categorized into 29 TFP food groups.[4] The categorization is illustrated in Fig. 2. For example, a 6 oz Yoplait Original Yogurt strawberry flavor is a UPC or barcode, with specific size and flavor information, which belongs to Yoplait Original (brand) Yogurt (product). Then Yoplait Original Yogurt brand-product belongs to the whole milk, yogurt, and cream food group. The variables σ, σ_g^a, and σ_g^w are the elasticities of substitution between food groups, across brand-products of food group g, and within a brand-product of food group g, respectively. The elasticities σ_g^a and σ_g^w are assumed to be constant for each food group g.

We use national expenditure shares to capture the importance of the availability of different UPCs, brand-products, and food groups in the variety index. The variable S_{bc} is the national expenditure share spent on the UPCs available in the local market c that fall within a specific brand-product category. Suppose, there are 10 UPCs of brand-product b available nationally, but only 4 of those UPCs are available in the local market. Then, the S_{bc} is calculated by dividing the national expenditure on the 4 UPCs of brand-product b by the national expenditure on all 10 UPCs of that brand-product. Analogously, S_{gc} is the national expenditure share spent on all brand-products within a

[2] As indicated in Eq. (1), the price in local market for UPC u is calculated by dividing the total local sales for UPC u by the total local quantities sold. Thus, if the same UPC is sold in two stores in the local market at different prices, the local price for the UPC is weighted by the quantities sold in each store.

[3] We include all stores in the local market into the price index calculation to depict the local retail market price that consumers face. In the price index, stores have already been weighted differently depending on the price and availability of products offered in the store.

[4] We categorize UPCs into different TFP groups rather than product groups as in Handbury and Weinstein (2014) because TFP nesting facilitates comparisons of price and variety differentials across nutritional categories. TFP nesting allows more meaningful comparison for within- versus between-variety comparison from a nutrition policy perspective when the groups are food groups recognized as key components of a balanced diet as opposed to arbitrary food groups selected for commercial purposes (product groups).

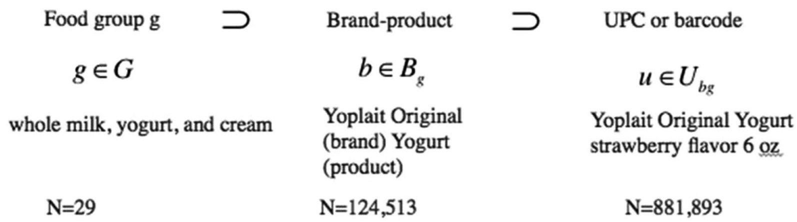

Fig. 2. Categories of foods.

specific food group that are available in the local market c. The variable S_c is the national expenditure share on the food groups available in the local market. The detailed equations used to calculate national expenditure shares S_{bc}, S_{gc}, and S_c are provided in Appendix B.

The variety-adjusted price index, EPI_c in the local market c is the product of $CEPI_c$ and VA_c:

$$
\begin{aligned}
EPI_c &= S_c^{\frac{1}{1-\sigma}} \prod_{g\in G_c} \left[CEPI_{gc} VA_{gc}\right]^{W_{gc}} \\
&= \prod_{g\in G_c} \left[CEPI_{gc}\right]^{W_{gc}} \left\{ \prod_{g\in G_c} \left[VA_{gc}\right]^{W_{gc}} \right\} S_c^{\frac{1}{1-\sigma}} \\
&= CEPI_c VA_c. \qquad (3)
\end{aligned}
$$

The $CEPI_c$ can be thought of as the correct way to measure the price level of the census tract if all UPCs are available in the local market. Since some local markets do not have all UPCs, brands, or food groups, we need to adjust the price index by the VA (VA_c). The VA consists of three availability indices. The UPC availability index of a census tract is given by $\prod_{b\in B_{gc}} (S_{bc})^{\frac{W_{bc}}{1-\sigma_g^w}}$, where variable S_{bc} provides a utility-adjusted count of missing UPCs in the local market c and the exponent weights the counts by how substitutable UPCs are (σ_g^w) and how important UPCs are in consumers' demand in the local market (W_{bc}).

The UPC availability index implies that if the local market misses a UPC with a large national expenditure share (S_{bc}), then the missing UPC is important in utility, and the VA and EPI will be higher. If the missing UPC is highly substitutable with other UPCs, then missing the UPC will not greatly affect the VA. The availability of a specific UPC in a census tract, for example, a 16 oz jar of Jif creamy peanut butter, will depend on the importance of this particular UPC and its substitutability towards other peanut butter UPCs that exist in the local market. If several important items in a food group are missing in a local market and hardly substitutable with existing items, then the EPI of that local market will be higher.

Similarly, the brand-product and food group availability indices ($S_{gc}^{\frac{1}{1-\sigma_g^a}}$ and $S_c^{\frac{1}{1-\sigma}}$) depend on the national expenditure shares of the brand-product and food group (S_{gc} and S_c), and whether the brand-product and food group have close substitutes (σ_g^a and σ). The more goods available in the local market, the lower the VA, and the closer the EPI is to the CEPI. Because one might believe that the lack of availability of whole food groups is a larger concern than the lack of a brand-products within a food group, we divide the VA into two components, namely, VA1 and VA2, that capture the across and within food group variety availability, respectively. The detailed expressions for VA1 and VA2 are provided in Appendix B.

After constructing the local market price indices, we compare the CEPI, VA, and EPI based on the following model:

$$
y_{ij} = \alpha_0 + \alpha_1 LA_{ij} + x_{ij}\beta + C_j + \varepsilon_{ij}, \qquad (4)
$$

where y_{ij} is the log of CEPI, VA, or EPI for local market i in county j. The indicator variable LA_{ij} take the value of one if the local market i in county j is a low-access area. The precise definition of low-access area is given in the data section. We also include observable demand side factors x_{ij}, i.e., income, poverty rate, population density, education, gender, marital status, age, and racial composition. In addition, we include county fixed effects (C_j) to control for county-specific demand shocks. The regression analysis allows us to study how stores' pricing behavior varies across neighborhoods with observably equivalent demand.

3. Data

We use IRI retailer scanner data (IRI InfoScan) from 15,722 stores in 10,367 census tracts in 2012 in the United States to construct the census tract level CEPI, VA, and EPI. The IRI InfoScan data are provided as a part of 2012 USDA National Household Food Acquisition and Purchases Survey (FoodAPS) and cover stores in the 50 Primary Sampling Units (PSUs).[5] In the context of this study, a PSU is defined as a group of adjacent sample counties (or, in some instances, individual counties) that is randomly selected from all counties in the U.S. According to Abadie et al. (2016), when data sampling is clustered, it is better to cluster standard errors at the sampling unit. Therefore, we cluster all standard errors at the PSU level when regressions

[5] The counties in the FoodAPS are nationally representative in terms of the number of SNAP households and non-SNAP households from three income groups: below 100% of the poverty threshold; between 100% and 184% of the poverty threshold, and equal to or greater than 185% of the poverty threshold.

analyses are performed. The IRI InfoScan provides weekly barcode level sales and quantity sold at each store or regional market area (RMA).[6–8] The data cover almost all major national and regional chain stores in the 84 sample counties.[9] We aggregate the IRI InfoScan data to an annual level, and calculate the national and local expenditure shares and prices subsequently as the building blocks for the price indices.

We define consumers' local market as their own and contiguous census tracts. The contiguous census tracts are those that share any boundary points with the census tract of interest. Based on FoodAPS data, households' average distance to the primary food store is 1.94 miles which is within the average radius of the contiguous census tracts (2.24 miles). Therefore, we use own and contiguous census tracts as households' primary shopping areas.

We categorize each UPC into different TFP food groups and brand-products within a TFP food group based on the product descriptions of UPCs. The TFP assigns weekly recommended consumption quantities of each food category for 15 age and gender groups based on the Dietary Guidelines for Americans and the My Pyramid Food Guidance System. The TFP is used to estimate the cost of a nutritious but cheap or "thrifty" diet and serves as the basis for the maximum Supplemental Nutrition Assistance Program (SNAP) monthly benefit. A full list of TFP categories and the weekly recommended pounds for a male aged 19–50 are provided in Appendix Table 1C. Because one TFP food group overlaps with several food groups from Handbury and Weinstein (2014), we use the average of σ_g^a and σ_g^w from the overlapping food groups in Handbury and Weinstein (2014) to estimate the elasticities of substitution within and across brand-products (σ_g^w and σ_g^a) for each TFP food group.

After constructing the local TFP EPI, we generate our main explanatory variable of interest, the food deserts indicator, defined as a low-income low-access census tract (USDA, 2013). A low-income census tract is defined as one that has either a poverty rate of 20% or higher, or a median family income at or below 80% of the area's median family income.

What constitutes access is debated in the food deserts literature. We define low-access census tracts as those with at least 500 people and/or 33% of the population residing more than one mile from a supermarket[10] in urban areas, where a supermarket is a store that has over 2 million annual sales and has all major food departments including fresh produce, fresh meat and poultry, dairy, dry and packaged foods, and frozen foods. We use this definition for two reasons. First, this definition is commonly used in the literature (e.g., Taylor and Villas-Boas, 2016; Thomsen et al., 2015) and allows us to compare our results to existing studies. Second, this definition is used for policy targeting. For example, the Federal Healthy Food Financing Initiative uses this definition to qualify projects expanding access to nutritious food in a food desert.

To define food deserts, we use access and income variables from USDA FoodAPS Geography Component (FoodAPS-GC) that are based on store lists from the 2012 TDLinx and STARS and income data from the 2008–2012 American Community Survey (ACS). We obtain other explanatory variables from the 2008–2012 ACS, i.e., family median income, poverty rate, race, gender, marital status, age, education, and population density.[11] Marital status and education are measured by the proportions of people who are married and have completed high school in the census tract and contiguous census tracts, respectively. We also include the proportions of males, children (age < 18), elderly (age ≥ 65), white, Hispanic, African American, and Asians in the census tract and contiguous census tracts. We use socioeconomic variables in resident and contiguous census tracts combined to allow for a flexible measure of local demand that accounts for the fact that households shop outside their census tract of residence into contiguous census tracts.

Next, we construct the average and median TFP cost by first calculating the average and median prices for each food group and use the county-level average and median prices to impute the prices of the missing food groups, where the average is the total expenditure divided by total pounds spent on the food group.[12] Then, we multiply the average and median price of each food group with the recommended pounds of consumption per week to get the average/median TFP cost. One key problem with the average or median TFP cost is that we need to impute the price of a missing food group in a census tract. Theoretically, the price for that missing product is infinitely large if no substitutes are available. This is one of the empirical challenges and motivations for the use of EPI, which employs economic theory to capture the effect of those missing food groups on overall prices.

Table 1 presents the summary statistics of the sample by income and access to supermarkets. All variables in Table 1 are calculated based on data both within the census tracts and contiguous census tracts. Out of the 84 sample counties, 63

[6] We include both random-weight food items (usually fresh produce) that have a pseudo UPC and nonrandom-weight food items (standardized food items) that have a unique UPC.

[7] Some store chains only provide weekly sales data at the RMA level. The RMAs of a store chain are aggregate geographical areas defined by the retailer and usually include several stores. Thus, the individual prices paid for a UPC cannot be identified at each store within a RMA. Therefore, we use the average price for the whole RMA to impute for each store and assume that if a UPC is sold in the RMA, then all stores in the RMA also sell that UPC at the same price.

[8] Private label information is only available for retailers that have individual store sales. The private label information is unavailable for RMA stores.

[9] The covered stores include stores of various types, i.e., merchandise stores, drug stores, convenience stores, dollar stores, grocery stores, and club stores. One drawback is that local independent stores and farmers' market are not included. However, the IRI states that around 80% of nationwide food at home expenditure is spent in stores covered by the IRI.

[10] The distance from a household to the nearest supermarket is measured by the distance from the centroid of the block groups where the household resides to the nearest supermarket and aggregates to the census tract level.

[11] We use 2008–2012 ACS for our socioeconomic variables to be consistent with our food deserts variables that are in part based on 2008–2012 ACS.

[12] There are 7,438, 1,810, 551, and 603 census tracts missing one, two, three, and over three TFP food groups.

Table 1
Summary statistics

	Food deserts	Low income high access	High income low access	High income high access
Average TFP cost	58.37	62.22	59.95	61.41
	(16.03)	(18.44)	(13.85)	(13.57)
Median TFP cost	97.32	103.73	105.14	108.70
	(17.61)	(18.26)	(14.06)	(13.41)
Number of TFP groups	28.34	28.11	28.59	28.65
	(1.38)	(2.04)	(1.29)	(0.99)
Number of UPCs	29677.73	27498.86	38856.69	38346.90
	(20078.12)	(18653.43)	(19044.73)	(17784.91)
VA1	0.89	0.90	0.89	0.89
	(0.02)	(0.19)	(0.03)	(0.02)
VA2	1.14	1.14	1.09	1.09
	(0.12)	(0.12)	(0.09)	(0.08)
VA	1.01	1.03	0.97	0.97
	(0.12)	(0.32)	(0.11)	(0.09)
CEPI	1.02	1.04	1.04	1.05
	(0.06)	(0.06)	(0.05)	(0.05)
EPI	1.04	1.08	1.01	1.01
	(0.18)	(0.38)	(0.15)	(0.13)
Having supermarkets	0.70	0.68	0.87	0.87
	(0.46)	(0.47)	(0.34)	(0.33)
Population density (persons/square mile)	4,535	15,507	3,100	9,617
	(4,054)	(15,827)	(2,662)	(13,174)
Married proportion	0.37	0.37	0.56	0.49
	(0.12)	(0.11)	(0.11)	(0.11)
Poverty rate	0.26	0.27	0.07	0.08
	(0.13)	(0.12)	(0.04)	(0.05)
Family median income ($)	42,715	42,532	102,402	92,839
	(14,364)	(14,773)	(40,442)	(33,301)
Children proportion (age $<$ 18)	0.26	0.26	0.23	0.21
	(0.09)	(0.08)	(0.06)	(0.06)
Elderly proportion (age $\geq$ 65)	0.12	0.10	0.14	0.14
	(0.11)	(0.06)	(0.09)	(0.08)
High school graduates proportion	0.75	0.70	0.93	0.90
	(0.14)	(0.15)	(0.06)	(0.08)
Male proportion	0.49	0.49	0.49	0.49
	(0.05)	(0.05)	(0.03)	(0.04)
African American proportion	0.26	0.21	0.07	0.09
	(0.28)	(0.29)	(0.14)	(0.16)
White proportion	0.31	0.23	0.68	0.52
	(0.30)	(0.22)	(0.26)	(0.28)
Hispanic proportion	0.31	0.35	0.13	0.20
	(0.24)	(0.22)	(0.14)	(0.16)
Asian proportion	0.03	0.07	0.08	0.13
	(0.05)	(0.13)	(0.11)	(0.15)
Obs.	923	3,468	2,113	3,863

Notes: Standard deviations are in the parentheses. Food deserts are defined as low-income urban census tracts where at least 33% or 500 people live over 1 mile away from supermarkets.

counties have all four types of census tracts and food deserts census tracts are usually spatially clustered in a county. Because a low-access census tract is one where over 33% or 500 people are over one mile away from the nearest supermarket, it is possible that a high-access census tract does not have a supermarket within itself or its contiguous census tracts if, for example, the census tract itself is very small. For similar reasons, a food desert can have supermarkets if the census tract is large and many people live in spots of the census tract that are far away from a supermarket. Nevertheless, as expected, we find that food deserts are less likely to have supermarkets than all types of nonfood deserts on average.

With respect to socioeconomic variables, food deserts have more unmarried, younger, less educated people, and more African Americans and Hispanics compared to High-Income Low-Access (HILA) and High-Income High-Access (HIHA) tracts. Low-Income High-Access (LIHA) tracts are more similar to food deserts across socioeconomic characteristics. These differences in demographic composition in census tracts imply that to study how stores' pricing behavior differ across neighborhoods, we need to control for socioeconomic characteristics that may affect preferences and demand.

4. Results

4.1. Main results

To compare the price indices between food deserts and non-deserts, we regress log of CEPI, VA, and EPI against indicator variables for LIHA, HILA, and HIHA census tracts. We find that the prices of food commonly available in both food deserts and nonfood deserts (CEPI) such as cheese, sweets, and coffee are similar between food deserts, LIHA, and HILA tracts. When comparing food availability, in Table 1 we find that food deserts and nonfood deserts have similar number of TFP food groups available but food deserts have almost 10,000 fewer UPCs than both HILA and HIHA tracts. However, these measures of variety availability do not account for the substitutability between food items or different importance of each food item in the consumer basket. After addressing both issues, we find the VA in food deserts is 1.1% lower in food deserts than LIHA tracts but 4.3% higher than HILA tracts in Table 2, with a higher VA indicating lower access to variety. Specifically, the major difference in varieties between HILA and food deserts comes from differences in within food group availability (VA2). Therefore, the variety-adjusted prices (EPI) are slightly lower (2.6%) in food deserts than LIHA tracts but 3.1% higher than HILA tracts in Table 2. The raw averages comparison in Table 2 gives us two key messages. First, the welfare impact of living in a food desert in terms of purchasing groceries seems to be small on average, as supported by the fact that the differences in food cost between food deserts and nonfood deserts are less than 4%. Second, as the price difference between food deserts and HILA tracts (income effects) is higher than that between food deserts and LIHA tracts (access effect), income matters more for the variety-adjusted prices than access before controlling for other demand factors.

In comparison, we find that in Table 1 the average and median TFP costs are actually lower in food deserts than all types of nonfood deserts tracts.[13] For example, the average and median TFP costs are 6% and 6.4% higher in LIHA compared to food deserts as shown in Table 2. This result may be caused by the fact that food deserts sell more lower-quality varieties of foods and thus prices are lower compared to nonfood deserts. Hence, if ignored, product heterogeneity and variety bias may mask a great deal of information in price comparisons, demonstrating the value of addressing both product heterogeneity and variety bias.

We find that consumers who may be limited in their shopping area face much higher prices in food deserts compared to those who can access stores in neighboring census tracts. Table 3 shows regression results of log EPI on LIHA, HILA, and HIHA tract dummy variables, excluding stores in contiguous census tracts. This analysis allows us to assess the food prices faced by consumers who are constrained to shop within stores in their census tracts, such as older adults with limited mobility or individuals that lack access to vehicles or public transportation. We find that those consumers in LA tracts face 9.2% higher prices than HA tracts.

Differences in the EPI may be due to differences in demand, supply/cost factors or both. Therefore, we control for observable demand factors and test whether food prices are still lower in low access areas when characteristics influencing demand are observably similar. Specifically, we regress log of CEPI, VA, and EPI against a low access dummy variable along with socioeconomic variables and county fixed effects that affect demand. Here, income variables are census tract family median income, which are continuous variables to better control for local demand factors.

We have three central findings from Table 4. First, the difference in EPI between low and high access tracts is only 3.5%, which is still small in magnitude. The majority of the small price difference comes from lower access to variety, particularly varieties of food items and brand-products within a food group (VA2), in low access tracts compared to high access tracts.

Second, the EPI is higher in low access tracts after isolating observable demand factors. The reversal in the sign from the simple averages to the regression results suggests that the access effect in the simple averages (Table 2) captures some of the income/demand effect. To compare the importance of different regressors, we calculate the standardized coefficients by scaling each regressor coefficient through multiplication with the standard deviation (SD) of the regressor divided by the SD of dependent variable (Kim and Feree, 1981). When comparing the standardized coefficients, we find that income is more important than access in associations with EPI, with standardized coefficients on tract median family income, poverty rate, and access of 0.107, 0.149, and 0.102, respectively. Interestingly, we find a significant racial disparity in EPI, where census tracts with high proportions of African Americans face significantly higher EPI, with standardized coefficient as high as 0.195. Furthermore, tracts with more higher educated people face significantly lower EPI, with the lowest standardized coefficient of –0.161. Thus, we find significant racial and educational disparity exist in terms of facing higher food prices. These large coefficients on demographic characteristics compared to coefficients on access provide suggestive evidence that demand is lower in food deserts, which translates into lower food prices as found in comparisons of raw averages.

Third, even though few large grocery stores exist in food deserts, we see little evidence of stores exhibiting market power.

[13] Notably, the average TFP cost is much lower than median TFP cost across all types of census tracts. It is because the average price for a TFP food group is calculated based on the total expenditure divided by total quantity sold, and is essentially an expenditure-weighted average price. If consumers spend most of their food expenditure on the cheaper items than more expensive items within a TFP group, then the cheaper items will have a larger weight in the average price than in the median price, resulting in a lower average price than the median price.

Table 2
Regressions on EPI without control variables

	Log CEPI	Log VA	Log VA1	Log VA2	Log EPI	Log average TFP cost	Log median TFP cost
LIHA	0.015***	0.011***	0.009***	0.002	0.026***	0.060**	0.064***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.005)	(0.029)	(0.018)
HILA	0.012***	−0.043***	0.002	−0.044***	−0.031***	0.039	0.083***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.006)	(0.024)	(0.012)
HIHA	0.021***	−0.044***	0.0002	−0.044***	−0.023***	0.064*	0.118***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.005)	(0.035)	(0.018)
Obs.	10,367	10,367	10,367	10,367	10,367	10,367	10,367

Notes: *, **, and *** denote significance levels at 0.1, 0.05, and 0.01, respectively. Standard errors are clustered at the PSU level and included in the parentheses.

Table 3
Regressions on EPI–Without contiguous census tracts sales

	Log CEPI	Log VA	Log VA1	Log VA2	Log EPI	Log average TFP cost	Log median TFP cost
LIHA	−0.007**	−0.085***	−0.004	−0.801***	−0.092***	0.061	0.004
	(0.004)	(0.013)	(0.007)	(0.010)	(0.015)	(0.054)	(0.052)
HILA	0.006	−0.097***	0.0001	−0.097***	−0.092***	0.148**	0.058
	(0.004)	(0.014)	(0.008)	(0.010)	(0.016)	(0.059)	(0.064)
HIHA	0.001	−0.156***	−0.011	−0.145***	−0.155***	0.215***	0.088
	(0.003)	(0.013)	(0.007)	(0.009)	(0.015)	(0.068)	(0.073)
Obs.	4,830	4,830	4,830	4,830	4,830	4,830	4,830

Notes: *, **, and *** denote significance levels at 0.1, 0.05, and 0.01, respectively. Standard errors are clustered at the PSU level and included in the parentheses.

Table 4
Regressions on EPI–With contiguous census tracts sales

	Log CEPI	Log VA	Log VA1	Log VA2	Log EPI
Low food access	0.009***	0.026***	0.004*	0.021***	0.035***
	(0.001)	(0.005)	(0.002)	(0.003)	(0.005)
Log tract median family	0.016***	0.013**	0.001	0.012***	0.029***
Income	(0.005)	(0.005)	(0.001)	(0.004)	(0.009)
Poverty rate	0.086***	0.089***	−0.003	0.092***	0.175***
	(0.017)	(0.026)	(0.006)	(0.022)	(0.036)
Population density	0.006***	0.014***	0.003	0.011***	0.020***
	(0.002)	(0.003)	(0.001)	(0.003)	(0.005)
Married share	−0.025**	−0.018	0.006	−0.023	−0.043
	(0.011)	(0.021)	(0.006)	(0.018)	(0.029)
Children share	−0.034**	0.011	0.004	0.007	−0.023
	(0.015)	(0.034)	(0.011)	(0.027)	(0.042)
Elderly share	0.004	−0.005	−0.011	0.006	−0.001
	(0.009)	(0.015)	(0.007)	(0.011)	(0.019)
High school share	0.025	−0.183***	−0.049***	−0.135***	−0.159***
	(0.019)	(0.025)	(0.016)	(0.014)	(0.020)
Male share	0.008	0.031	0.013	0.018	0.039
	(0.014)	(0.031)	(0.011)	(0.026)	(0.042)
African American share	0.026**	0.097***	0.001	0.097***	0.124***
	(0.012)	(0.026)	(0.012)	(0.020)	(0.028)
White share	0.037***	0.037	0.002	0.035*	0.074**
	(0.012)	(0.027)	(0.012)	(0.019)	(0.031)
Asian share	0.027	0.017	−0.010	0.026	0.044
	(0.020)	(0.037)	(0.015)	(0.023)	(0.048)
Hispanic share	0.025	0.008	−0.013	0.021	0.033
	(0.020)	(0.035)	(0.015)	(0.023)	(0.040)
Obs.	10,367	10,367	10,367	10,367	10,367

Notes: *, **, and *** denote significance levels at 0.1, 0.05, and 0.01, respectively. Standard errors are clustered at the PSU level and included in the parentheses. County fixed effects are also included.

Table 5
Regressions on EPI–How much difference do supermarkets make?

	With supermarkets			Without supermarkets		
	Log CEPI	Log VA	Log EPI	Log CEPI	Log VA	Log EPI
Low food	0.003***	0.005***	0.008***	0.0004	0.008	0.008
Access	(0.001)	(0.001)	(0.001)	(0.002)	(0.007)	(0.007)
Log family	0.015***	0.007***	0.022***	0.010*	0.014*	0.024**
Income	(0.006)	(0.001)	(0.006)	(0.005)	(0.007)	(0.011)
Poverty rate	0.079***	0.031***	0.110***	0.008	0.004	0.011
	(0.010)	(0.008)	(0.015)	(0.014)	(0.025)	(0.036)
Obs.	8,213	8,213	8,213	2,154	2,154	2,154

Notes: *, **, and *** denote significance levels at 0.1, 0.05, and 0.01, respectively. Standard errors are clustered at the PSU level and included in the parentheses. Race, gender, marriage, age, education, and population density in the census tracts and contiguous census tracts as well as county fixed effects are included. Log family income is log tract median family income.

Table 6
Regressions on EPI–Commonly available foods

	Log CEPI	Log VA	Log EPI
Low food access	0.004***	0.007***	0.011***
	(0.001)	(0.001)	(0.002)
Log family income	0.006***	0.003***	0.010***
	(0.002)	(0.001)	(0.003)
Poverty rate	0.032***	0.023***	0.055***
	(0.007)	(0.007)	(0.012)
Obs.	10,367	10,367	10,367

Notes: *, **, and *** denote significance levels at 0.1, 0.05, and 0.01, respectively. Standard errors are clustered at the PSU level and included in the parentheses. Race, gender, marriage, age, education, and population density in the census tracts and contiguous census tracts as well as county fixed effects are also included. Log family income is log tract median family income.

When demand is observably similar, stores charge only slightly higher prices in low access areas where they face little local competition. In addition, we find from FoodAPS data that the average food desert household travels as far as 2.6 miles to their primary grocery store, and over 95% of the households choose cheap supermarkets as their primary store type, which moderates the effect of local supply conditions and may contribute to the small market power of local stores.

To check whether the difference in EPI is driven by the existence of nearby supermarkets, we compare the prices only for the census tracts with supermarkets in the local market and those without supermarkets in the local market in Table 5. We find that CEPI, VA, and EPI are similar in low access and high access tracts when both have only small stores around or when both have supermarkets in the local market. Thus, the higher EPI in low access tracts found in Table 4 largely comes from those low access tracts without a supermarket nearby versus high access tracts with a supermarket nearby. These results suggest that neither supermarkets nor nonsupermarkets charge higher EPI in low access tracts compared to high access counterparts. But low access tracts are less likely to have supermarkets which, in turn, have higher VA than nonsupermarkets. In sum, the lack of supermarkets leads to higher EPI in low access tracts than high access counterparts.[14] Nevertheless, given the difference in EPI between low and high access tracts is only 3.5% on average, encouraging supermarkets entry into food deserts may have limited effects of lowering food prices and improving healthy eating.

Lastly, we test to see if higher prices are driven by higher prices of goods in convenience stores in Table 6. We calculate and compare the EPI for the six most commonly available TFP food groups,[15] which are available in both traditional grocery stores and convenience stores. Results show that even after accounting for different access to variety, the EPI of commonly available food groups in low access tracts is almost the same as high access tracts. Thus, we find our results do not merely reflect higher prices for processed foods in convenience stores in food deserts; instead, they reflect higher prices in items that are not generally found in convenience stores such as fruits and vegetables, which supports that food deserts have both higher prices and lower availability of healthy foods.

4.2. Robustness tests

We conduct five robustness tests and the results are shown in Appendix D. All robustness tests results are consistent with our main findings. First, we demonstrate results without county fixed effects in Appendix Table D1. Second, one may be concerned that using the average elasticities of substitution in overlapping Handbury and Weinstein (2014) food groups overestimate the degree of substitutability within a TFP food group.[16]

[14] We recognize that the prices consumers pay are related to store/brand searching ability (Binkley, 2013). In this article, we focus on the exogenous prices consumers face (i.e., stores pricing behavior) and leave how store/brand search behavior affects the extent to which consumers benefit from lower prices due to availability for future research.

[15] The six TFP food groups are "nonwhole grain breads, cereal, rice, pasta, pies, pastries, snacks, and flours," "fruit juice," "all cheese, including cheese soups and sauces," "nuts, nut butters, and seeds," "coffee and tea," and "sugars, sweets, and candies."

[16] If the products within a TFP food group are less substitutable than the elasticity of substitution suggests now, then food deserts that miss a lot of UPCs would be penalized more in the EPI calculation and actually have higher EPI than what's currently estimated. Thus, our estimates provide a lower bound.

Thus, we test the robustness of our results against other estimates of elasticities of substitution in Appendix Table D2. Specifically, we use 4 and 7 as the across and within brand elasticities of substitution, which are commonly used in marketing literature (Dube and Manchanda, 2005).

Third, one may be concerned that we cannot compare the same UPCs for the random-weight items, especially something like produce, which arguably hinders our ability to adjust for product heterogeneity. Thus, we test the veracity of our results when random-weight items are excluded in Appendix Table D3.

Fourth, one may wonder that census tract plus the contiguous census tract may not be the correct spatial unit to describe the retail environment. Thus, we test the robustness of our results using a more general area surrounding a census tract as consumers' shopping area. Appendix Table D4 provides the results when we allow consumers to shop within a two-mile buffer zone of the resident census tract, where 2 mile is the 75 percentile of the distance to a primary grocery store from the FoodAPS data. The EPI difference between low and high access census tracts becomes even smaller when the two-mile definition of local market is used.

Lastly, in Appendix Table D5, we study the store coverage of IRI data compared with TDLinx, the most complete list of food stores at the census-tract level in the U.S. and is widely used by the industry to analyze the regional retail market. We find that at the census tract level, on average IRI covers over 90% of club stores, mass merchandisers, dollar stores, and drug stores. But the coverage of grocery stores (74% and 75% in store counts and sales) and convenience stores (53% and 57%) is lower. While we do not anticipate that including more stores would have an impact on our substantive conclusions, an expansion of the IRI data set to include more stores would help address this issue.

5. Conclusion

In this article, we construct a price index that adjusts for both product heterogeneity and variety bias to compare the local cost of a nutritious diet in food deserts versus nonfood deserts. We find that after controlling for observable demand, the stores charge slightly higher price (0.9%) and have lower food availability (2.6%) in low access tracts than in their high access counterparts. In combination, the variety-adjusted price index is only 3.5% higher in low access areas. The small difference in EPI between food deserts and nonfood deserts suggests both limited market power of existing stores in food deserts and a relatively small welfare impact of living in a food desert, at least for those who can travel to neighboring census tracts to shop. Consequently, while higher food prices are associated with higher rates of food insecurity (Gregory and Coleman-Jensen, 2013; Hassan, 2016), our results suggest that living in a food desert is unlikely to influence food insecurity to a great extent, at least in as much as substitute foods are available. (For more on food insecurity in the United States, see Gundersen and Ziliak, 2014 and Gundersen et al., 2011.)

Our results are influenced by how we define the "local" grocery market. For households who are constrained to buy food within their resident tracts, the variety-adjusted price index is 9.2% higher in low access tracts than high access counterparts. This result implies that those households who are constrained to shop within their resident census tracts are much more affected by living in a food desert.

Our results suggest that when observable demand is equivalent, higher prices in low access tracts are driven by the lack of supermarkets. On one hand, the small price difference induced by the presence of supermarkets suggests that policies aimed at improving access alone may not be effective in lowering food prices or improving diets. On the other hand, we emphasize that demand-side factors such as income and poverty rate are important to consider. So efforts to increasing the purchasing power in these areas may be worthwhile to pursue. For example, increasing benefits and participation rates in the Supplemental Nutrition Assistance Program (SNAP, formerly known as the Food Stamp Program) may have greater impact on food insecurity and dietary outcomes of households in food deserts than food desert policies themselves, insofar as SNAP has consistently been demonstrated to increase the purchasing power of low-income households (Bartfeld et al., 2015; Gundersen et al., 2017; Ziliak, 2016).

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Online Appendix