Access to Local Agriculture and Weight Outcomes

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Recent studies examine the impact of the built environment on health outcomes such as obesity. Several studies find for certain populations that access to unhealthy food has a positive effect on obesity, whereas access to healthy choices has a negative effect. Given the growth and popularity of locally grown food, we examine how individual weight outcomes are affected by access to direct-to-consumer local food. After controlling for potential endogeneity, we find that greater access to local food has a negative association with individual weight outcomes. We also find a negative association with greater weight loss over a one-year period. These results provide evidence that local food access can have potential indirect benefits.

Key Words: local agriculture, obesity, food access

The obesity crisis in the United States has led researchers and public interest groups to identify contributing factors to obesity, resulting in an extensive list of potential candidates. One factor that has received increasing attention in the U.S. is access to food. Food access in the U.S. entails not only physical accessibility, but also distinguishing between low- and high-quality food, where quality is generally defined by nutritional content. An important question is whether there is sufficient access to high-quality food in the U.S. to foster healthy weight outcomes. To this end, we must examine how access to different types of food affects weight outcomes.

Several studies find that access to low-quality food away from home, particularly fast-food restaurants, has a positive effect on rates of obesity. Chou, Grossman, and Saffer (2004) find that the per capita number of fast-food restaurants has a significant impact on obesity levels. Currie et al. (2010) find that fast-food availability significantly affects the percentage of ninth-grade students who are obese and the weight gain of pregnant mothers within select demographic groups. Additionally, Dunn (2010) finds at the county level that availability of fast-food restaurants contributes to increased body mass index among females and non-whites in medium-density counties.

Alternatively, a few studies have found that access to higher-quality food such as in supermarkets has a negative association with rates of obesity. Morland, Wing, and Roux (2002) note an increase in fruit and vegetable intake corresponding to each additional supermarket within a census tract (a 32 percent increase for black Americans and an 11 percent increase for white Americans). Similarly, Morland, Roux, and Wing (2006) find a lower (higher) prevalence of obesity associated with the presence of supermarkets (convenience stores). Presumably, supermarkets offer more healthy choices than convenience stores.

Locally grown food is another source of high-quality food for which significant interest has grown over recent years (Brown and Miller 2008, Darby et al. 2008).[1] While access to local food could contribute to consumer health, there has been limited research examining this relationship. In one recent paper, Salois (2012) examines the relationship of several measures of the local food economy and rates of obesity. He finds a negative relationship between local food establishments and aggregate county-level measures of obesity.

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[1] We consider local food to be locally grown and processed agricultural products and marketed direct-to-consumer. This is in contrast to agriculture that is distributed through a supply chain.

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In this article, we examine the effect of access to direct-to-consumer local food on individual weight outcomes as measured by body mass index (BMI) for individuals in the northeast United States. We also examine how access impacts individual weight loss. To measure access to local food we identify the number of community-supported agriculture (CSA) groups and farmers markets (FM) at the county level. We combine this with the Behavioral Risk Factor Surveillance System (BRFSS), which provides a cross-section of individual health outcomes and demographic characteristics. We also employ instrumental variable methods to correct for the potential endogeneity of local food access. For instruments, we use several measures of county-level agricultural production that are correlated with local agricultural production that would supply CSAs and FMs but do not directly impact individual weight outcomes. Based on several statistical tests, it appears that our instruments adequately explain the endogenous variables and are sufficiently orthogonal to the model error as well.

In general, we find that access to direct-to-consumer local food has a negative association with weight outcomes as measured by BMI. We also find that access to local food is associated with higher levels of individual weight loss over a one-year period. We estimate several model variations and find that our results are robust across different specifications. Overall, the results of our estimates are consistent with other studies that find a negative relationship between access to healthy foods and weight outcomes. Whereas it is more common to think of food access in terms of the built environment, i.e., restaurants and grocery stores, this research highlights the importance of considering alternative forms of food access.

Motivation

Food access impacts the total cost to obtain food products. Limited access to some food products increases the cost to obtain that food, whereas increased access reduces the cost. An increase in food access is effectively equivalent to a price reduction since, holding all else constant, supply is increasing. As such, food access affects whether or not a food product will enter an individual's choice set and, ultimately, whether or not he will choose the product. Given this choice decision, we can then determine how food access affects weight outcomes.

The effect of food access on weight outcomes depends on how increased food access affects total demand for food and the quality of the food that is ultimately consumed. Consider some individual that consumes a vector of n food products $x' = (x_1, x_2, ..., x_n)$. Each element of x contributes to the total amount of nutrition, N, consumed by the individual according to a vector of nutritional characteristics that corresponds to each food product, $\alpha' = (\alpha_1, \alpha_2, ..., \alpha_n)$, such that $N = \alpha' x$. For simplicity, we will focus on one dimension of nutrition that affects weight outcomes: calories.[2] Therefore, N is a linear function of the foods being consumed, x, such that $N = \alpha_1 x_1 + \alpha_2 x_2 + \alpha_n x_n$. In this simple example, as N increases so does an individual's weight outcome. This is clearly a basic view of nutrition, but can be used in this context without loss of generality.

If access for good 1 (x_1) increases, we would expect consumption of x_1 to increase. At question is how all other goods respond to a change in the price of good 1. We can take the derivative of N with respect to the price of good 1—

$$(1) \qquad \frac{\partial N}{\partial p_1} = \alpha_1 \frac{\partial x_1}{\partial p_1} + \alpha_2 \frac{\partial x_2}{\partial p_1} + ... \alpha_n \frac{\partial x_n}{\partial p_1}$$

—then decompose the price effect using the Slutsky equation to obtain

$$(2) \qquad \frac{\partial N}{\partial p_1} = \alpha_1 \left[\frac{\partial h_1}{\partial p_1} - x_1 \frac{\partial x_1}{\partial I} \right] + \alpha_2 \left[\frac{\partial h_2}{\partial p_1} - x_2 \frac{\partial x_2}{\partial I} \right] + ... \alpha_n \left[\frac{\partial h_n}{\partial p_1} - x_n \frac{\partial x_n}{\partial I} \right].$$

The first term in each bracket is the substitution effect where h is Hicksian demand, and the second term is the income effect where I is income. We are interested in the outcome when increased food access for good 1 (which lowers the price) leads to fewer calories and a lower weight outcome:

[2] In reality, the vector α is a matrix of values which translate x into a vector of nutrition values, $\vec{N}$.

$$\frac{\partial N}{\partial p_1} > 0 .$$

This occurs when

$$-\alpha_1 \left[\frac{\partial h_1}{\partial p_1} - x_1 \frac{\partial x_1}{\partial I} \right] < \sum_{i=2}^{n} \alpha_i \left[\frac{\partial h_i}{\partial p_1} - x_i \frac{\partial x_i}{\partial I} \right].$$

That is, the *increase* in consumption for good 1, weighted by its caloric value (α_1), must be compensated with an aggregate *decrease* in consumption of all other goods, weighted by their caloric values (α_i).

The left-hand-side bracket is unambiguously negative, as a price decrease leads to greater consumption (assuming that good 1 is a normal good). Whether or not the inequality holds depends on how all other goods respond to the price change. We decompose the effect for different types of goods in Table 1. In general, if increased access to good 1 leads to an increase in complementary consumption, this will lead to a higher weight outcome. If increased access to good 1 causes substitution from other goods, the effect on weight outcome will depend on the caloric content of the substitute goods relative to good 1. If good 1 is more caloric, then substituting to good 1 will result in a higher weight outcome. If good 1 is less caloric, then substituting to good 1 will result in a lower weight outcome.

In practice, if local food is less caloric than an individual's average consumption, we might expect a lower weight outcome for that individual given greater access to local food. At the same time, however, increased access to local food may lead consumers to substitute away from low-calorie foods they already purchase at retail grocery chains. As suggested by Currie et al. (2010), although fast food is unhealthy, access to fast-food restaurants could just allow consumers to substitute away from unhealthy foods at home to unhealthy foods at restaurants. Anderson and Matsa (2011) also suggest that consumers offset calories from restaurant meals by eating less at other times. Consumption of local food does not necessarily guarantee lower weight outcomes if its caloric content is equivalent to substitute goods.

Further, increased access to local food could result in increased consumption of substitute goods (if the income effect dominates the substitution effect as shown in the bottom of row 3 on Table 1). This would occur if increased access to local food allowed an individual to consume local food *and* consume more junk food as well. Such an effect would result in a higher weight outcome.

While there have been claims that local food is more nutritious than other types of food,[3] the impact of local food on weight outcomes is still ultimately an empirical question.

Local Food Markets

Local food appeals to health-conscious consumers concerned about not only the methods and technology used to grow or produce their food, but from where and whom their food comes. Further, local food provides consumers the opportunity to connect with the farmer, the land, and the community. As a specific example, Slow Food International, a group dedicated to local food, is interested in counteracting "fast food and fast life, the disappearance of local food traditions and people's dwindling interest in the food they eat, where it comes from, how it tastes and how our food choices affect the rest of the world."[4] Some local food groups even promote the consumption of local food over food grown by large-scale agricultural systems, claiming its inherent superiority (Born and Purcell 2006). Whether or not this is accurate remains to be seen; however, increased consumption of local food promotes, among other things, the consumption of fresh produce, which can contribute to a healthier lifestyle.

Local food can be accessed by consumers through several channels. One marketing channel for local food that has grown considerably over the past decade is Community-Supported Agriculture (CSA). In general, CSAs are a contract between a farmer and consumer, where the consumer pays up front for the delivery of fresh, local produce throughout the year.[5] As defined by the U.S. Department of Agriculture, "community supported agriculture consists of a community of

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[3] The Harvard Medical School's Center for Health and the Global Environment discusses this issue at http://chge.med.harvard.edu/programs/food/local.html (June 18, 2011).

[4] Taken from www.slowfood.com.

[5] In examining the data used in this study, we see that CSAs can involve agreements for non-produce items as well, such as beef, honey, or eggs. The majority of CSAs we looked at, however, deal with produce.

Table 1. The Effect of Increased Access for Good 1 on Different Types of Food Products

Type of good	Substitution Effect: $\frac{\partial h_i}{\partial p_1}$	Income Effect: $\frac{\partial x_i}{\partial m}$	Total Response to Price Change	Marginal Change in N
(1) Normal complement	(-)	(+)	(-)	$N\uparrow$
(2) Inferior complement	(-)	(-)	$\frac{\partial h_i}{\partial p_1} > x_i \frac{\partial x_i}{\partial I}$: (-)	$N\uparrow$
			$\frac{\partial h_i}{\partial p_1} < x_i \frac{\partial x_i}{\partial I}$: (+)	$N\downarrow$
(3) Normal substitute	(+)	(+)	$\frac{\partial h_i}{\partial p_1} > x_i \frac{\partial x_i}{\partial I}$: (+)	$N\downarrow$
			$\frac{\partial h_i}{\partial p_1} < x_i \frac{\partial x_i}{\partial I}$: (-)	$N\uparrow$
(4) Inferior substitute	(+)	(-)	(+)	$N\downarrow$

Notes:
Row 1: Consumption of normal complements will increase, which will marginally increase N.
Row 2: Consumption of inferior complements will increase if the substitution effect dominates the income effect (top of row 2) and decrease if the income effect dominates (bottom of row 2).
Row 3: Consumption of normal substitutes will decrease if the substitution effect dominates the income effect (top of row 3) and decrease if the income effect dominates the substitution effect (bottom of row 3).
Row 4: Consumption of inferior substitutes will decrease, which will marginally decrease N.

individuals who pledge support to a farm operation so that the farmland becomes, either legally or spiritually, the community's farm."[6] The CSA farmer sells individual shares for some upfront investment and in return provides a portion of output during the growing season. The number of shares in each CSA can range from a few dozen to a few hundred, depending on the size of the CSA. In terms of growth, Brown and Miller (2008) estimate that CSAs have grown from roughly 50 in 1990 to roughly 1,900 in 2008.

Farmers markets (FMs) are another marketing channel for local food that has grown significantly over recent years. Based on the USDA definition, an FM is "a retail outlet in which two or more vendors sell agricultural products directly to customers through a common marketing channel" (Ragland and Tropp 2009, p. 13). Participants of FMs generally operate booths or stands allowing consumers to select from their offering of products. While FMs are most popular in the summer months, more are stretching out their seasons into the fall and spring months by holding their markets indoors. According to the USDA's Agricultural Marketing Service, the number of FMs tripled from 1994 to 2010.[7] FMs often allow for payment via government programs such as the Women, Infants, and Children (WIC) program, the Farmers Market Nutrition Program, and the Supplemental Nutrition Assistance Program (SNAP), making them accessible to a wide range of consumers.

The growth in CSAs and FMs represents a growing interest in local food. While individuals can often purchase local food from other sources such as retail outlets or restaurants, CSAs and FMs allow a unique opportunity to connect with the growers. At the same time, CSAs and FMs vary in terms of the way they interact with consumers. CSAs require more active engagement and generally require some commitment by the participant. This can often be through required labor in addi-

[6] Taken from the USDA's National Agricultural Library website: www.nal.usda.gov (August 1, 2011).

[7] Taken from http://www.ams.usda.gov/AMSv1.0/farmersmarkets (June 18, 2011).

tion to paying dues. Additionally, Thompson and Coskuner-Balli (2007) describe an enchantment associated with joining a CSA. Farnsworth et al. (1996) find that CSA shareholders place value on knowing that the products they purchased are chemical-free, knowing the farmer who grew their food, supporting a localized food system, and reestablishing a rural connection.

FMs, on the other hand, are much more passive in their interaction with consumers. Consumers who attend FMs are not obligated to make any purchases or even interact with growers in any way. As such, while both represent the growth of demand for local food, they also represent different perspectives on the local food experience.

Data

We use the Centers for Disease Control and Prevention's (CDC) (2009) Behavioral Risk Factor Surveillance System (BRFSS) Selected Metropolitan/Micropolitan Area Risk Trends (SMART) data, which measures a number of individual health behaviors and outcomes, including body mass index (BMI), which is computed as

$$\text{BMI} = 703 \times \left(\text{weight (lbs)} \div \text{height (in)}^2\right).$$

The CDC conducts telephone interviews and gathers data on height and weight, which it uses to calculate the BMI for each individual. We gather data on CSAs and FMs in New England, which is the focus of our analysis (Table 2).

The CDC samples from a subset of the total number of counties in each state and identifies individuals at the county level. As can be seen in Table 2, the average BMI is approximately the same across states and, except for those from Massachusetts, the minimum and maximum values are similar as well. The BRFSS also provides an extensive amount of individual demographic information, including age, number of children in household, education level, household income, and gender.[8] The data also describe whether or not the individual is currently retired. In addition to demographic variables, there are several health indicators provided by the BRFSS. *Diabetes* and *cholesterol* identify whether the individual has been informed that he has either health issue. *Heart disease* is calculated based on whether the individual has ever had a myocardial infarction, angina, or coronary heart disease, or a stroke.

Diabetes, cholesterol levels, and heart disease could simultaneously be determined with BMI. For some, however, these health conditions are the result of genetic traits and not just behavioral choices. If they are genetically determined, they would not be endogenous in our models. This is unlikely, however, for *all* survey respondents with these health conditions. Retirement is often an endogenous choice variable as well, such as when a person stops working for health issues. It can also be an outcome of an individual reaching retirement age. Accounting for these health variables and retirement can help differentiate between different types of individuals. At the same time, it can add unwanted bias to our model. As such, we estimate models with and without these potentially endogenous variables to determine how they impact our estimates.

As our dependent variable is BMI, we may bias our estimates by including individuals in our analysis who are affected by random events such as illness or non-random events such as pregnancy, both of which lead to non-random lifestyle changes that skew weight outcomes. As such, we drop individuals from our sample who are pregnant, who have cancer or have had cancer in the past five years, or who are limited in any activities because of physical, mental, or emotional problems. We also drop those with arthritis that limits or alters their lifestyle, as they are likely to be more sedentary.

To measure the extent of local agricultural access in a given state, we count the number of CSAs and FMs in each county. There is no official federal registry for CSAs or FMs, although many states have organizations dedicated to promoting and sustaining both. One organization, Local Harvest, provides CSAs and FMs nationwide the opportunity to register on their website (localharvest.org) free of charge. From their website, we acquire an initial count of the number of CSAs and FMs by zip code.[9] We then identify the loca-

[8] The original dataset included individuals who were in their nineties. These individuals may lack mobility and therefore are unable to capitalize on food access. We therefore restrict the dataset to those under sixty-six years of age. Doing so did not significantly affect our primary findings.

[9] We thank Local Harvest for granting permission to analyze data harvested from their website.

Table 2. State-Level Statistics and Demographic Information for Study Sample

		States					
		CT	ME	MA	NH	RI	VT
Counties in study		5	5	9	5	4	6
Counties in state		8	16	14	10	5	14
CSAs		38	119	95	51	20	48
FMs		84	48	168	59	35	52
Sample population		2,379	1,753	6,653	1,870	2,574	1,911
BMI DATA	Mean	26.48	26.97	26.72	26.89	26.94	26.53
	St. dev.	4.97	5.07	5.14	5.06	5.21	5.23
	Min.	16.00	13.70	7.85	16.47	13.76	17.20
	Max.	54.99	53.11	57.08	54.64	58.71	59.73
AGE	Mean	46.10	47.84	45.99	47.61	46.10	47.51
	St dev.	11.61	10.85	11.39	11.03	11.46	11.06
	Min.	18.00	18.00	18.00	18.00	18.00	18.00
	Max.	65.00	65.00	65.00	65.00	65.00	65.00
CHILDREN	Mean	0.84	0.77	0.89	0.79	0.85	0.77
	St. Dev.	1.09	1.07	1.12	1.07	1.10	1.05
	Min.	0.00	0.00	0.00	0.00	0.00	0.00
	Max.	7.00	7.00	9.00	7.00	7.00	6.00
EDUCATION	Mean	5.34	5.21	5.17	5.27	5.15	5.22
	St Dev.	0.91	0.89	1.01	0.88	0.97	0.91
	Min.	never	never	never	never	never	elementary
	Max.	4 yrs. of college or more					
INCOME	< $10k	1.92%	2.42%	2.74%	1.45%	2.60%	2.14%
	$10k to < $15k	2.30%	3.71%	3.47%	2.21%	3.61%	3.07%
	$15k to < $20k	4.34%	5.10%	5.78%	4.85%	5.38%	3.91%
	$200k to < $25k	5.41%	5.90%	7.84%	6.21%	7.43%	5.97%
	$25k to < $35k	8.24%	10.55%	9.99%	8.72%	9.32%	10.13%
	$35k to < $50k	11.76%	17.08%	12.83%	14.24%	14.58%	17.11%
	$50k to < $75k	16.99%	21.20%	15.86%	18.28%	19.23%	21.14%
	> $75k	49.04%	34.03%	41.49%	44.05%	37.85%	36.53%
Female		56.49%	59.04%	59.54%	58.07%	59.75%	55.68%
Diabetes		6.73%	6.56%	7.00%	6.63%	6.57%	5.29%
Heart disease		2.27%	2.57%	2.93%	2.99%	2.72%	2.56%
Retired		5.34%	5.70%	4.85%	6.47%	5.67%	4.66%

tion of each CSA and FM by county. Each state in our study has a department of agriculture that also tracks FMs and CSAs. We use their data to supplement the Local Harvest data. In cases where the data match, we make no changes. In cases where there is a difference, we compare the two lists for consistency and make adjustments. Using both the state lists and Local Harvest, we are able to identify FMs and CSAs that are still operational. Using these sources, we develop an approximation of CSAs and FMs by state (Table 2). As can be seen, Massachusetts has the largest number of FMs, as well as CSAs and FMs combined. Maine has the largest number of CSAs, and Rhode Island has the fewest of both CSAs and FMs. There is concern about whether or not the registered CSAs and FMs found on Local Harvest's website are representative of the total number for each state. Since registration of CSAs and FMs is voluntary, Local Harvest provides free advertising, which should create a strong incentive to register. Additionally, by using state department of agriculture data, we are able to verify these estimates.

One important question is whether measuring the count of CSAs and FMs provides an acceptable approximation of the prevalence of local food within a county. CSAs and FMs vary by size; however, their size is likely to change periodically. Even if we had a measure of CSA shares and FM vendors, there is no guaranteeing that the number would represent an equilibrium capacity. Implicitly we are assuming that the formation of CSAs and FMs is more likely to occur in counties where local food is both popular and organized, and that the count of CSAs and FMs is an adequate estimate of their popularity.

To normalize the number of CSAs and FMs across counties, we use two different approaches. First, we normalize by county square miles and then by county population per square mile. Each normalization procedure provides a different approximation to access. We discuss the different estimates in the results section.

Empirical Approach

Our primary interest is to determine what effect access to local food has on individual weight outcomes. If individuals have greater access to local food, the cost of obtaining local food is reduced. However, as previously discussed, the effect of greater access to local foods on weight outcomes depends on individual consumption of *all* food items. Since we observe only weight outcomes and access to local food, we estimate a reduced-form model to test if there is a significant relationship between the two. Combining our BRFSS data with our estimates of county-level CSAs and FMs, we estimate the following cross-sectional model:

$$BMI_{ik} = \sum_{s=1}^{6} \alpha_s \times d_{si} + \beta \times CSA_k + \gamma \times FM_k + \Gamma \times Z_{ik} + \varepsilon_{ik}, \tag{3}$$

where for each individual i in county k the dependent variable is *BMI*, and the variables CSA_k and FM_k are used to specify the number of CSAs and FMs, respectively, in county k. β, γ, and Γ are parameters to be estimated, and ε_{ik} is an iid error term. The term Γ is conformable to Z_{ik}, which includes several individual demographics described in Table 2. Age, education, income, and number of children may have a quadratic relationship with *BMI*. We explicitly test for this effect in our estimation.

To account for variation based on location differences, we cluster individuals by their state (s) using state-level fixed effects, which we identify using a dummy indicator variable d_{si}. α_s are parameter estimates of the state fixed effects. There is likely to be additional variation between counties as well; however, because the number of CSAs and FMs is county-invariant, we cannot identify those parameters specifying county-level fixed effects. To account for unobserved effects at the county level, we therefore cluster our standard error estimates by county.

Identification

This analysis attempts to estimate the effect that the supply of local food has on obesity. CSAs and FMs are likely to be established in areas where there is adequate demand for their product. Omitted covariates in the error term that affect BMI may be correlated with the establishment of local food—particularly if local food has an effect on caloric intake. If there are unobserved determinants of BMI that are also correlated with the variables CSA_k and FM_k, we would underestimate the effect of CSA_k and FM_k on BMI.

There are different approaches to dealing with potential endogeneity. Anderson and Matsa (2011) and Dunn (2010) explicitly attempt to account for the endogeneity of fast-food restaurant availability using access to interstate highways as instrumental variables. Alternatively, rather than employ instrumental variable estimates, Currie et al. (2010) rely on research-specific identifying assumptions to support their estimates of the effect of fast-food access.

We first test for endogeneity to determine if instrumental variable methods are necessary. If they are not necessary, then OLS estimates are preferred to instrumental variables. Specifically, we employ a Durbin-Wu-Hausman (DWH) procedure. First, we separately estimate CSA_k and FM_k as a function of all exogenous variables and our instrumental variables. We then take the residuals from these estimated models, insert them into equation (3), and test the significance of the residual terms (i.e., whether they are significantly different from zero). If they are significantly different, this is an indication of endogeneity.

We use three measures of county-level commercial agricultural production taken from the 2007 Census of Agriculture as instruments (Table 3). The number of farms and average farm sales excludes direct sales to consumers (e.g., CSA and FM sales), and therefore measure only commercial agriculture. There are several ways that these instruments may explain the number of CSAs and FMs. Counties with greater amounts of agricultural production (i.e., average sales) are likely to have more available resources (knowledge, capital, labor) to help support CSAs and FMs (Low and Vogel 2011). Further, a larger number of farms may provide cost economies that could benefit CSAs and FMs. Alternatively, as Low and Vogel explain, local food sales tend to be higher in metropolitan areas with fewer commercial farms. They suggest that the high price of land near metropolitan areas may only allow for small-scale farms providing higher-valued, niche products. Consequently, a greater number of acres in cropland may be related to fewer CSAs and FMs. After estimating these models, we test for the strength of these instruments at explaining the endogenous variables.

Table 3. Instrumental Variables, Their Description, and Sources

Variable	Description
Farms	Number of farms selling agricultural products in 2007 (less direct sales)
Average farm sales	Average sales of farm products in 2007 (less direct sales)
Acres	County cropland in acres 2007

Source: 2007 Census of Agriculture, available at http://www.agcensus.usda.gov/.

For the instruments to be effective, we must also be sure that they are orthogonal to the error term. If the instruments are correlated with other unobserved factors, then instrumental variable estimates would be worse than OLS. Our instruments measure commercial agriculture production and not agricultural products provided directly to consumers living near the farms. Therefore, the instruments would not directly impact individual rates of obesity. As noted by a reviewer, however, one particular concern is that commercial agriculture reflects county population density. Healthier individuals may choose to move to (or from) population-dense areas for health-related reasons such as access to open space and recreation or better access to facilities. If this is the case and commercial agriculture effectively measures how population-dense an area is, then the instruments will not be orthogonal to the error term. Dunn (2010) investigates a similar issue with using interstate exits as instrumental variables for fast-food restaurants. The interstate exits may measure unobserved urban characteristics that impact individual location selection.

There are several reasons why we expect that our instrumental variables are not correlated with our error term. First, the literature to date provides mixed evidence as to whether population density is related to increasing or decreasing obesity [Plantinga and Bernell (2007), Eid et al. (2008), and Zhao and Kaestner (2010) document an extensive literature arguing both sides]. As such, there is reason to doubt a non-random relationship between population density and obesity in our sample. It is important to note, however, that the most recent work on this subject, by Zhao and Kaestner (2010), suggests that lower population density *is* causally related to obesity. Still, they do not identify the particular mechanism that leads to this outcome. Clearly, heterogeneous location differences play a more important role in affecting obesity than just population density differences.

Secondly, commercial farm production does not necessarily equate with greater rural space for people to live or recreate in. Nor do fewer commercial farms indicate a dearth of recreational activities. Residential landscapes are more complex than just a simple rural/urban indicator, as important spatial interactions will play a role as well. As noted in Dunn, Sharkey, and Horel (2012), rural areas cannot be treated as uniform, as there are differences in resources and even daily commuting patterns that may be more relevant to consider. That is, an individual living in a population-dense county may still have access to rural landscapes. Overall, our contention is that our instrumental variables are orthogonal to our error terms and sufficiently related to our endogenous variables.

Empirical Findings

We estimate equation (3) using several different specifications using OLS with robust standard errors clustered by county. For models 1 and 2 we normalize CSAs and FMs per square mile (Table 4, columns 1 and 2). We find that age and age-squared are both significant and suggest an inverted u-shape as individuals get older. We find similar results with education, highlighting declining returns to education as the level of education increases. The number of children and children-squared are also significant but have a u-shape, indicating that the rate of weight outcomes increases as the number of children increase. There are similar findings with income. Finally, as expected, women have on average a lower BMI than men. These demographic variables are consistent across all four models. Although they are likely to be endogenous, cholesterol, diabetes, and heart disease are all positively related to BMI, as expected. Adding these covariates does not appear to impact the primary findings of the models.

In models 1 and 2, the parameter estimates for CSAs and FMs are significantly negative, indicating that greater access to CSAs and FMs in *geographic* terms is related to lower weight outcomes. That is, as access per square mile increases, weight outcomes decrease. Based on our theoretical model, this suggests that increased access to local food is associated with overall lower caloric consumption. This would be due to individuals substituting local food for higher caloric foods as access for local food increases.

The magnitude of the effect for CSAs is much larger than FMs in both models. This implies that access to CSAs is associated with lower levels of BMI. Consumers purchase CSA shares before harvest, sometimes even before planting occurs. As such, the commitment to CSAs can have a more direct impact on consumer purchases since a portion of their income is allocated to local food in advance, reducing their disposable income. Further, purchasing shares from a CSA guarantees that a consumer will have local food available to them. This may compel consumers to consume more local food and less of other types of food. Alternatively, FMs are an open market where consumers may interact with a limited number of vendors, or none at all. Therefore, access to FMs does not necessarily guarantee that a consumer will purchase any local food. Further, FMs often provide high-calorie local foods (pastries, prepared dishes, etc.) as well as local produce, whereas CSAs are generally committed to providing produce.

To put the effect of local food on weight outcomes into perspective, we perform a simple exercise. The average number of CSAs in each county is 10.9 and the maximum number in any county is 49, roughly 4.5 times larger. The average number of CSAs per square mile is 0.0173. Using the model 1 estimate of CSAs per square mile (-15.06), a 4.5-fold increase in CSAs per square mile corresponds to a -0.91 change in BMI.[10] Translating this -0.91 difference in BMI into weight using the average height for males in our sample (5 ft 7 in) and the BMI calculation results in a 5.82 lb decrease in weight. This is a 3.05 percent decrease in weight based on the average weight for males in our sample (191 lbs). While this does not imply a causative effect of CSAs on weight loss, the simple calculation does illustrate the difference in weight outcomes associated with the presence of CSAs.

We also estimate models where we normalize the number of CSAs and FMs using population per square mile (Table 4, rows 3 and 4). The parameter estimates of the covariates do not change significantly. The estimates of FMs are insignificant. The estimate of the CSA parameter in model 4 is significant and *positive*, but only at a 10 percent level and including the endogenous covariates (cholesterol, diabetes, heart, retired).

[10] A 4.5-fold increase would result in 0.0779 CSAs per square mile. The impact of this increase on BMI would then be (0.0779 – 0.01733) × -15.06 = -0.91.

Table 4. Estimates of Equation (3) Using OLS

	Dependent Variable = BMI			
Variables	(1)	(2)	(3)	(4)
Age	0.237***	0.152***	0.235***	0.151***
	(0.0291)	(0.0416)	(0.0288)	(0.0418)
Age^2	-0.00245***	-0.00186***	-0.00242***	-0.00185***
	(0.0003)	(0.0005)	(0.0003)	(0.0005)
Children	-0.535***	-0.608***	-0.533***	-0.603***
	(0.1340)	(0.1340)	(0.1360)	(0.1380)
Children^2	0.0874**	0.107***	0.0891***	0.107***
	(0.0324)	(0.0341)	(0.0318)	(0.0340)
Education	1.567***	1.593***	1.648***	1.657***
	(0.2590)	(0.3810)	(0.2480)	(0.3740)
Education^2	-0.238***	-0.237***	-0.248***	-0.245***
	(0.0268)	(0.0388)	(0.0258)	(0.0382)
Income per member	-0.561***	-0.622***	-0.544***	-0.605***
	(0.1580)	(0.1470)	(0.1610)	(0.1490)
Income^2	0.0564***	0.0635***	0.0539***	0.0611***
	(0.0163)	(0.0152)	(0.0168)	(0.0155)
Gender (female = 1)	-1.638***	-1.549***	-1.643***	-1.551***
	(0.0982)	(0.0948)	(0.0966)	(0.0934)
Cholesterol		1.323***		1.328***
		(0.1100)		(0.1100)
Diabetes		3.258***		3.260***
		(0.1850)		(0.1850)
Heart		0.404*		0.408*
		(0.2150)		(0.2110)
Retired		-0.153		-0.151
		(0.1740)		(0.1750)
FMs per sq mile	-1.746***	-1.856***		
	(0.3960)	(0.3990)		
CSAs per sq mile	-15.06***	-13.50**		
	(5.4770)	(4.9550)		
FMs per person per sq mile			-0.792	-0.838
			(1.0160)	(0.7650)
CSAs per person per sq mile			1.7540	1.949*
			(1.5500)	(1.0990)
Constant	23.67***	25.68***	23.23***	25.25***
	(0.8350)	(1.0640)	(0.8180)	(1.0490)
Observations	17,140	15,258	17,140	15,258

Notes: Standard errors are in parentheses. Standard errors are clustered by county. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

Assuming that food access is both a function of physical distance and population density, these two approaches for normalization have varying interpretations, particularly since we do not know precisely where individuals in our sample live in each county. Normalizing by square miles implicitly assumes that CSAs and FMs are uniformly distributed (geographically) across a county. This normalization will overestimate access to CSAs and FMs for individuals who actually live in parts of the county with few CSAs and FMs, and will underestimate access for those who live in parts with many CSAs and FMs. For example, an individual in our sample may live in a part of the county with no CSAs or FMs. Normalizing by square miles, we artificially allocate CSAs and FMs to that individual.

Alternatively, normalizing by population per square mile implicitly assumes that CSAs, FMs, *and* county population are uniformly distributed across a county. As such, this approach will underestimate access to CSAs and FMs for individuals who actually live in low population parts of the county, and will overestimate access for individuals who actually live in high population parts. For example, an individual may have access to several CSAs or FMs, but normalizing by population per square mile artificially allocates population density. This effectively reduces the calculated measures of CSAs and FMs.

With our research question and data, it is unclear which one of the two methods of normalization is preferable.[11] Intuitively, this type of research may be better served by more detailed spatial analysis—for example, using distance measures or nearest neighbor approaches. As noted by Dunn (2010) in his work on fast-food access, however, spatial analysis still involves certain assumptions. Measuring exposure to fast food using the distance from home to fast-food locations precludes the impact of those who live far from fast food but drive by many restaurants on the way to work. He suggests that the "precise definition of availability may be of second-order importance, since a greater number of restaurants lowers the distance [to fast-food restaurants] for at least some residents" (p. 1150). He finds little difference comparing his county-level data to the zip code level data which provides more accurate measures of proximity. Food access can also be affected by physical limitations such as crime, public transit access, and physical impediments. Bader et al. (2010) use detailed GIS mapping to incorporate such access limitations into their analysis of New York City. Such an effort over multiple states, as in our analysis, would require a much more extensive database and greater spatial complexity. Our county-level measure of CSAs and FMs normalized per square mile provides an initial approximation of individual access to local food.

Instrumental Variables Approach

As previously discussed, we anticipate possible endogeneity with our measures of local food. We test for endogeneity using the previously described DWH test. We find evidence that the number of CSAs is endogenous, while the number of FMs is not. To account for bias caused by endogeneity in our model, we estimate equation (3) using GMM and the previously discussed instrumental variables.[12] We focus on the model where CSAs and FMs are normalized using square miles.

Comparing the GMM estimates in Table 5 to the OLS estimates reveals the degree to which OLS estimates are biased and underestimate the impact of the local food access. Adjusting for this bias results in a larger estimate of the relationship of local agricultural access and BMI. The magnitude of the covariates does not change significantly and the overall implications of the results are similar to the OLS models. Using a similar calculation as before, the presence of CSAs is now associated with a 14.2 lb decrease in weight, or approximately 7.46 percent of the weight of an average male in the sample.

[11] An anonymous reviewer suggested that per capita normalization might be superior to per square mile because CSAs and FMs tend to locate relatively near more urban areas. Examining a map of CSAs and FMs suggests that this may not be entirely correct. There tends to be slightly more FMs near major urban areas, but FMs are also present in non-urban areas. Further, CSAs tend to be more evenly distributed across states. In the literature, we have observed both approaches for normalization. Dunn (2010) normalizes using population; Bader et al. (2010) normalize using per square kilometer. Without knowing the exact location of our sample population within a county, neither approach appears to be superior for our study.

[12] We test our instrumental variables for under-identification and weak identification using standard tests offered in STATA version 10.1 (Cragg and Donald 1993, Kleibergen and Paap 2006). Our first-stage estimates suggest that the instrumental variables are sufficiently strong and identified. We also fail to reject the null for Hansen's J-test for over-identification.

Table 5. Estimates of Equation (3) Using GMM

	Dependent Variable = BMI	
Variables	(5)	(6)
Age	0.239***	0.154***
	(0.0263)	(0.0315)
Age^2	-0.00247***	-0.00188***
	(0.0003)	(0.0003)
Children	-0.528***	-0.604***
	(0.1070)	(0.1120)
Children^2	0.0843***	0.105***
	(0.0284)	(0.0298)
Education	1.482***	1.517***
	(0.3600)	(0.4080)
Education^2	-0.227***	-0.228***
	(0.0374)	(0.0420)
Income per member	-0.567***	-0.629***
	(0.1090)	(0.1170)
Income^2	0.0574***	0.0647***
	(0.0115)	(0.0122)
Gender (female = 1)	-1.635***	-1.548***
	(0.0754)	(0.0785)
Cholesterol		1.324***
		(0.0873)
Diabetes		3.257***
		(0.1940)
Heart		0.384
		(0.2460)
Retired		-0.159
		(0.1620)
FMs per sq mile	-2.535***	-2.823***
	(0.8090)	(0.8520)
CSAs per sq mile	-36.83***	-34.04***
	(7.9420)	(8.1240)
Constant	24.09***	26.09***
	(1.0160)	(1.2110)
Observations	17,140	15,258

Notes: Robust standard errors are in parentheses. *** indicates p < 0.01, ** indicates p < 0.05, and * indicates p < 0.1

Robustness Checks

Although the estimated results suggest that access to CSAs and FMs is associated with lower rates of obesity, our cross-sectional data provide no indication of the trajectory of rates of obesity for any individual, only a single period measurement. Weight outcomes can take time to develop and are the result of many factors. As suggested by Dunn, Sharkey, and Horel (2012), the relationship between obesogenic exposure and weight, which is a stock variable, may be more susceptible to omitted variable bias. Consequently, it may be more relevant to examine the effect of food access on changes in flow variables, such as consumption. As previously discussed, increased access to one type of food can affect consumption of all foods. Therefore, it would be relevant to assess how increased access to local food impacts the flow of *total* consumption, which we do not observe. We can instead estimate the relationship of access to local food and individual weight change. While our data is limited to one time period, the BRFSS respondents report their change in weight over the course of one year. The weight change variable better represents the cumulative impact of local food access on total consumption. That is, if total consumption changes due to increased access, we are likely to observe any effect through changes in weight. Specifically, we estimate

$$(4)\qquad \Delta weight_{ik} = \sum_{s=1}^{6} \alpha_s \times d_{si} + \beta \times CSA_k + \gamma \times FM_k + \Gamma \times Z_{ik} + \varepsilon_{ik},$$

where $\Delta weight_{ik} = weight_{ik,t} - weight_{ik,t-1}$.

The results in Table 6 (model 7) show that greater access to CSAs per square mile is associated with greater weight loss for individuals over a one-year period. That is, a larger number of CSAs is associated with individuals who have experienced a larger (negative) weight change over the past year. Based on our theoretical motivation, if consumers are substituting to lower-calorie local foods, we would expect a weight change over time. These estimates provide more support for the possibility that access to CSAs is associated with improved weight outcomes.

We find that the effect of FMs per square mile is associated with a significant weight *gain*. As

Table 6. Estimates of Equation (3) Using Sample That Lost Weight, Maintained Weight, and Gained Weight

	Dependent Variable = Weight Change		
Variables	Full Sample (7)	< 55 (8)	> = 55 (9)
Age	-0.249***	-0.429***	0.0899
	(0.0711)	(0.1290)	(0.1540)
Age^2	0.00251***	0.00498***	-0.000556
	(0.0008)	(0.0017)	(0.0011)
Children	1.148***	1.354***	0.15
	(0.3080)	(0.3570)	(0.5790)
Children^2	-0.272***	-0.310***	0.00906
	(0.0916)	(0.0955)	(0.2190)
Education	0.525	2.223	-0.406
	(1.8640)	(2.3960)	(1.1900)
Education^2	-0.0488	-0.228	0.0717
	(0.1850)	(0.2390)	(0.1270)
Income per member	-0.275	-0.41	0.302
	(0.2650)	(0.3850)	(0.3820)
Income^2	0.0183	0.0385	-0.0401
	(0.0294)	(0.0410)	(0.0401)
Gender (female = 1)	0.462**	0.506*	0.512***
	(0.1790)	(0.2520)	(0.1850)
FMs per sq mile	2.098***	1.421	0.336
	(0.6310)	(0.8550)	(0.6000)
CSAs per sq mile	-21.34**	-31.83***	2.152
	(7.9190)	(10.3300)	(8.5790)
Constant	3.348	2.412	-5.838
	(5.4260)	(6.6160)	(6.2180)
Observations	17,140	12,215	9,231

Notes: Standard errors are in parentheses. Standard errors are clustered by county. *** indicates $p < 0.01$, ** indicates $p < 0.05$, and * indicates $p < 0.1$.

previously mentioned, this could be due to the fact that FMs offer other foods besides produce and CSAs tend to offer only produce. At the same time, this result could be influenced by characteristics of our survey sample. People's bodies tend to change significantly around middle age. For example, Williams (1997) found that middle-aged men are susceptible to weight gain regardless of their level of physical activity. Further, Brown et al. (2005) found that after adjusting for physical activity and energy imbalance, middle-aged women tend to have yearly weight gain associated with hysterectomy, menopause, and quitting smoking. Consequently, middle-age weight change may be symptomatic of unobserved characteristics. To examine this, we estimate equation (4) using the sub-samples of individuals above and below 55 years of age (models 8 and 9).[13] We find a difference in the effect of CSAs and FMs on these two sub-samples. CSAs still have a significant effect on weight loss for those under 55 but not over, and the effect of FMs is insignificant for both groups. Overall, it appears that access to CSAs is positively related to greater weight loss, at least for populations under middle age.

[13] These results are robust to defining middle age as being from 40 to 60 years old.

As noted by a reviewer, purchases made from CSAs and FMs are smaller than purchases from other sources such as fast food or grocery stores. Our estimates stand out in contrast to smaller or negligible effects found in the fast food literature. It is likely that the effect of local food access that we identify may represent some unobserved latent characteristics in the market. As one example, greater numbers of CSAs and FMs could increase market competition and drive down prices for fruits and vegetables, which would lead to greater consumption and potentially impact health outcomes. This is similar to the relationship of population density and obesity found by Zhao and Kaestner (2010). Although they establish a negative causal link, the underlying mechanism relating the obesity and population density is not clear.

Conclusions

Access to healthy food is a highly relevant and timely topic. According to the Behavioral Risk Factor Surveillance System (BRFSS), at least 55 percent of the population of every state is categorized as overweight or obese, with the highest percentage being 70 percent in Mississippi. At the same time, more evidence is emerging that food access and the built environment have an impact on consumer health in terms of rates of obesity. If food access affects consumer behavior and ultimately consumer health outcomes, then providing adequate access to healthy food can have important implications for dealing with obesity in the United States.

The current literature has focused on the built environment (stores, restaurants, etc.). This paper makes an attempt to connect direct-to-consumer local food and individual weight outcomes. According to our theoretical motivation, access to local food improves weight outcomes if it allows consumers to substitute away from higher-calorie foods. Our results provide some evidence that the number of CSAs and FMs per square mile is associated with lower individual weight outcomes. Additionally, the number of CSAs is associated with greater decreases in weight over a one-year period. Since purchases of local food are relatively small, the effect we identify may be representative of some unobserved latent characteristic in the market. This deserves greater exploration with finer-level data.

Given the growth and popularity of the local food movement over recent years, it could be valuable to find ways to help facilitate its development, especially if there are positive spillover effects. One way to do this is to begin gathering more data on the scale, scope, and location of local food organizations. Such information is useful in determining how to efficiently use available resources or where potential opportunities may exist. It may be helpful to find ways to connect consumers with local agriculture as well. If access to unhealthy food choices, which seem ubiquitous, is related to higher levels of obesity, it is important to find ways to increase access to healthy food choices.

Our results highlight a limitation to our study stemming from data availability. We do not know exactly where individuals live in a county. As such, we define food access at a county level, which is a simplistic view of an individual's access to food. Further, using county-level data requires that we normalize between counties. We use two different normalization approaches: per square mile and population per square mile. The results of these different approaches reveal the sensitivity to our assumptions. Finally, we do not account for other impediments that affect food access. Future research will benefit from developing more accurate measures of food access.

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