Obesity and Diabetes, the Built Environment, and the 'Local' Food Economy

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1 December 2010

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Abstract

Obesity and diabetes are increasingly attributed to environmental factors, however, little attention has been paid to influence of the 'local' food economy. This paper examines the association of measures relating to the built environment and the ‘local’ food economy with county-level prevalence of obesity and diabetes. Key indicators of the ‘local’ food economy include the density of farmers’ markets, volume of direct farm sales, and presence of farm-to-school programs. This paper employs a robust regression estimator to account for non-normality of the data and to accommodate outliers. Overall, the built environment is strongly associated with prevalence of obesity and diabetes and a strong 'local' food economy may play an important role in prevention. Results imply considerable scope for community-level interventions.

Keywords: community-level intervention, diabetes, food environment, famers’ market, leverage points, local food, robust regression, obesity, outliers.

1. Introduction

Poor dietary choices are associated with obesity, diabetes, and other chronic diseases that are leading causes of death such as heart disease, stroke, and cancer (McGinnis and Nestle 1989). Much of the existing research focuses on the role of individual-level factors and examines how dietary choices and health are affected by demographic and socioeconomic characteristics such as education, employment, ethnicity, and income (Dowler 2001; Davey Smith and Brunner 1997). While research into individual-level factors is important, interventions supported by this research have had limited success (Elinder and Jansson 2008; Egger and Swinburn 1997). More recently, the influence of the built environment and other geographical factors has received considerable attention.

The literature highlights the importance of community-level factors as explanations of dietary choices (Morland et al 2002) and diet-related health outcomes, such as obesity and diabetes (Morland et al. 2006; Mobley et al. 2006). Evidence suggests the built environment, and the food environment especially, play a strong role in influencing obesity (Feng et al. 2010). Food environmental factors shown to be important include the density of restaurants, including fast-food outlets and full-service venues, as well as the density of retail food stores, including supermarkets and convenience stores. Reviews of the existing literature suggest more research on the influence of the built environment on health is needed, particularly research emphasizing the potential of broad-based community-level interventions (Holsten 2008; Papas et al. 2007).

While many features of the built environment have been examined, little attention in the literature has been given to the possible influence of the 'local' food economy. The term 'local' means foods that have been sourced locally from farms and usually refers to a distance (e.g. within 50 miles) or a political boundary (e.g., within county borders). The hallmark of the local food economy is the farmers' market, although Community Supported Agriculture programs, and other outlets like roadside stands, small and independent grocers, and direct farm sales are also examples (Adams and Salois 2010). In a recent report from the Centers for Disease Control (CDC) on recommended strategies to prevent obesity, one suggestion was that communities should improve ways to bring food from "farm to fork" more directly and effortlessly, namely through increased density of farmers' markets (Kettle Kahn et al. 2009). To date, only a small handful of studies examine the presence of 'local' foods on dietary outcomes (Anliker 1992; Balsam 1994; Herman et al 2008), and none directly on health outcomes. Results support the idea that farmers' markets improve dietary choices by enhancing the availability of affordable healthy foods, such as fresh fruits and vegetables (Larsen and Gilliland 2009). There is a clear need, however, for research into how 'local' foods may influence dietary health outcomes, such as obesity and diabetes.

The objective of this study is to examine how the built environment affects the prevalence of obesity and diabetes, paying special attention to the impact of the 'local' food economy. Including an extensive set of environmental indicators is essential for assessing simultaneous effects of different indicators on both obesity and diabetes. Focusing on particular indicators in isolation, such as fast food restaurants, can yield misleading results and incorrect policy conclusions. Environmental indicators include measures relating to socioeconomic status, geography, physical activity, and the food environment. Indicators on the strength of the 'local' food economy include the density of farmers' markets, the strength of direct farm sales, and farm-to-school programs. Robust regression is used to account for non-normality of the data and to accommodate outliers in the dependent and independent variables. Parameter estimates using linear least squares can behave badly when the regression residuals are not normally distributed, especially when a heavy-tailed distribution is present. This problem often occurs in aggregate data because outlying observations are present. While the removal of such influential points is a common practice, a better approach is to apply an estimation method that handles fat-tailed error distributions without throwing away valuable information. Robust regression handles non-normal residuals and protects against influential observations.

Results reveal substantial influence of the built environment on obesity and diabetes prevalence and suggest wide scope for community-level interventions. Possible interventions include community-wide programs to develop a strong ‘local’ food economy through creation of farmers' markets, farm-to-school-programs, and enhanced direct farm sales. Other strategies involve improving food access by enhancing transportation options to low-income residents. This paper is organized as follows. The next section explains the robust regression estimator. Section 3 describes the data. Section 4 discusses the major results of the paper. The final section offers policy recommendations and concludes.

2. Estimation Strategy

Ordinary least squares (OLS) estimates are driven by the assumption of normally distributed residual error terms. If the residuals are characterized by a fat-tailed non-normal distribution, then OLS estimates are inefficient. Fat-tailed residual distributions can arise when outliers are present in the data. In general, two types of outliers may occur, which in general involve a data point that substantially deviates from the expected value (Rousseeuw and Leroy 1987). The first type occurs on the dependent variable and is referred to as a vertical outlier. The second type occurs on the explanatory variable and is called a leverage point. Either type falls under the umbrella of being an influential observation and can strongly impact OLS estimates. Since the undue influence of select data points may not be desirable, alterative estimation strategies should be sought (see Dehon et al. 2009 for a good discussion on the impact of vertical outliers and leverage points on point estimates). One of the more common approaches is to simply delete the influential observations. Although a common practice, throwing away outlying observations is a mistake since these observations are often the most important (Zaman et al. 2001). Influential data points, both outliers and leverage points, should be appropriately handled in the econometric model and not tossed out.

Robust regression estimators accommodate fat-tailed error distributions and provide parameter estimates resistant to influential observations. Ideally, they also maintain efficiency in the presence of non-normality, though not all have this desirable property. There are several types of robust estimators which operate by giving less weight to observations that are further from the expected value. Consider the following linear regression model

$$y_i = X_i^{'}\beta + \varepsilon_i, \tag{1}$$

for the i^{th} observation where $i = 1,\ldots,n$. In addition, y is the $n \times 1$ dependent variable vector, X is the $n \times m$ independent variable matrix, β is the $m \times 1$ vector of parameters to be estimated, m is the number of independent variables where $m = 1,\ldots,M$, and ε is the $n \times 1$ residuals vector. The OLS estimator obtains parameter estimates by minimizing the sum of the squared errors

$$Min\sum_{i=1}^{n}\left(e_i^2\right). \tag{2}$$

When the residuals are very large, the OLS error variance is inflated which results in inflated standard errors. The efficiency of the estimator is also negatively affected by the error variance inflation.

Robust estimators are not as vulnerable as least squares to this type of problem. One such type estimator is the least absolute deviation (LAD) estimator. Parameter estimates from LAD are based on the optimization

$$Min\sum_{i=1}^{n}\left|e_i\right|, \tag{3}$$

which is merely the median regression, a special case of the quantile regression estimator. Since LAD is based on absolute deviations, it tends to be less sensitive to outliers in the dependent variable than OLS. In addition to LAD, Huber (1973, 1981) developed the class of M-estimators, based on a generalization of the quadratic specification in equation (2)

$$Min\sum_{i=1}^{n}\rho\left(e_i\right), \tag{4}$$

where ρ is some function (typically convex) that provides the contribution or weight of the i^{th} residual to the minimization problem. A valid ρ is symmetric ($\rho(e)=\rho(-e)$) and positive ($\rho(e)\geq 0$), with a unique minimum at zero ($\rho(0)=0$). Parameter estimates are calculated using an iterative weighted least squares process. The initial fit is calculated first to obtain an updated set of estimated weights. The process then iterates until convergence of the parameter estimates is achieved.

While LAD and M-estimators provide a level of protection against vertical outliers, neither can accommodate unusual leverage points, meaning large deviations in X_i from the expected value (Rousseeuw 1984). The concept of breakdown point was introduced by Hampel (1971) to describe how robust an estimator is to aberrant data points. The breakdown point is the smallest percentage of contaminated data that can cause an estimator to take on unusually large values. The maximum breakdown point for an estimator is 50% since if more than half the observations are contaminated it then becomes impossible to differentiate the underlying distribution from the contaminated distribution. The mean has a breakdown point of 0% while the median has a breakdown point of 50%. In regards to vertical outliers, the OLS estimator has a breakdown point of zero. While LAD and M-estimators achieve a higher breakdown point for vertical outliers, both have a low breakdown point for leverage points.

To handle the dual problem of both vertical outliers and leverage points, the class of MM-estimators was developed (Yohai 1987). MM-estimators combine high breakdown value estimation and efficient estimation. MM-estimators build upon the class of S-estimators proposed by Rousseeuw and Yohai (1984). Unlike S-estimators, however, MM-estimators maintain high efficiency when the residuals are normally distributed. MM-estimation proceeds in three stages. In the first stage S-estimation is used, then in the second stage a robust M-estimate is computed based on the initial S-estimate residuals, and finally in the third stage the regression parameters are computed based on an M-estimator. MM-estimation maintains the efficiency of M-estimation while achieving the robustness of S-estimation to influential points.

The MM-estimator is given by

$$Min\sum_{i=1}^{n}\rho\left(\frac{e_i}{\hat{s}}\right) \tag{5}$$

where $\hat{s}$ is a robust scale estimate for the residuals and ρ is typically defined as the bisquare function. Parameter estimates are obtained through iterative weighted least squares. The key difference from the M-estimator is the inclusion of the scale parameter, $\hat{s}$, which is used to standardize the residuals and is obtained with the S-estimator. Differentiating with respect to the coefficients and setting partial derivatives to zero yields the $k+1$ system of equations

$$\sum_{i=1}^{n}\varphi\left(\frac{y_i - X_i^{'}\beta}{\hat{s}}\right)X_i = \sum_{i=1}^{n}w_i\left(\frac{y_i - X_i^{'}\beta}{\hat{s}}\right)X_i = 0\,. \tag{6}$$

where φ is the derivative of ρ. The weighting function is defined as $w(e,\hat{s}) = \varphi(e,\hat{s})/e$ so that $w_i = w(e_i,\hat{s})$. The derivative, φ, measures the influence of each observation on the value of the parameter estimate and is called the influence function (Hampel 1974). For example, in OLS the objective function is $\rho(e) = \frac{1}{2}e^2$, which implies an influence function of $\varphi(e) = e$ and a weighting function of $w(e) = 1$. This means that the influence of each observation increases linearly with the size of the error. Clearly, OLS is not a robust estimator since the influence function for OLS is unbounded; only one influential observation is needed to ruin OLS estimates. In the case of LAD, the objective function is $\rho(e) = |e|$, which implies an influence function of $sign(e)$ and a weighting function of $1/|e|$. While the influence of outliers is mitigated using LAD, since ρ is not strictly convex, the estimator is unstable. Also, since the second derivative is unbounded at zero an indeterminate solution could occur.

The bisquare ρ-function is used in the MM-estimator

$$\rho(e) = \begin{cases} \frac{k^2}{6}\left\{1-\left[1-\left(\frac{e}{k}\right)^2\right]^3\right\} & for\ |e| \le k \\ \frac{k^2}{6} & for\ |e| > k \end{cases}, \tag{7}$$

which yields the weighting function

$$w(e) = \begin{cases} \left[1-\left(\frac{e}{k}\right)^2\right]^2 & for\ |e| \le k \\ 0 & for\ |e| > k \end{cases}. \tag{8}$$

The weights for the bisquare function decline as e moves away from zero. The tuning constant for the bisquare is $k = 4.685\sigma$ which produces 95% efficiency at the normal. The MM-estimator achieves both a high breakdown point (50%) and high efficiency (95%). In other words, the MM-estimator can cope with data contamination up to 50% of the sample but still achieve asymptotic efficiency of 95% even if the errors follow a normal distribution. Therefore, although they tend to be more computationally intensive, they also provide the best level of protection against influential data points in terms of efficiency. Under the usual regularity conditions, MM-estimators are strongly consistent and asymptotically normal, with variance depending only on the limiting value of the scale estimator ($\hat{s}$).

3. Data Description

County-level data are primarily from the Food Environment Atlas published by the Economic Research Service (ERS) of the U.S. Department of Agriculture (USDA). The Atlas provides statistics on three main categories: health environment, food environment, and community environment. The health variables include measures of healthy diets, physical activity, and prevalence of adult obesity and diabetes. The food choice variables indicate the level of access to different foods, and include measures such as the density of grocery stores, supercenters, and convenience stores. Community characteristics include measures such as race/ethnicity, income, and poverty, among others. The data in the Atlas are sourced from different government entities for all 3,141 U.S. counties. This study only included counties in the continental U.S. and omitted counties with missing information ($n = 3{,}051$). Table 1 lists the variables included in this study along with the year, the original data source, and descriptive statistics. Two health outcome measures are investigated: county rates of obesity and diabetes. The obesity rate is the age-adjusted percentage of adults (age $\geq$ 20) with body mass index (BMI) greater than or equal to 30. Body mass index is computed by dividing weight in kilograms by height in meters squared. The diabetes rate is the age-adjusted percentage of adults with diabetes, excluding gestational diabetes. The rates of obesity and diabetes are based on estimates from the CDC, obtained from the Behavioral Risk Factor Surveillance System (BRFSS).

County-level variables describing the food environment can be partitioned into three general categories: eating-out food environment, retail food environment, and the ‘local’ food environment. The eating-out environment is indicated by the density of full-service and fast-food (or limited-service) restaurants, both defined as the number of restaurants per 1,000 persons. Full-service restaurants are defined as establishments that provide food services to customers on the basis of a waiter/waitress service (i.e., customers are seated while ordering and being served food and then pay after eating). Fast-food restaurants are defined as establishments that provide food services to customers on the basis that food is ordered and paid for before eating.

The retail food environment is indicated by the density of supermarkets and grocery stores, gas-based convenience stores, no-gas convenience stores, and supercenters/warehouse clubs, where density is the number of outlets per 1,000 persons. Grocery stores are defined as establishments typically referred to as supermarkets and also include small-end grocery stores that retail food as their primary business function (this included delicatessen-type outlets that satisfy this requirement). Gas-based convenience stores are defined as establishments engaged in selling fuel or gasoline but also sell a selection of limited food items. No-gas convenience stores are defined as establishments that retail a limited selection of food items but do not sell fuel or gasoline. Supercenters and warehouse clubs are defined as establishments that in addition to retailing food and groceries, also sell merchandise including clothing, furniture, and electronics.

The 'local' food environment is indicated by the percent of direct-sale farms, the value of direct farm sales per capita, the density of farmers' markets, and the presence of a farm-to-school program. The percent of direct sale farms is defined as the percent of farms in the county that sell directly to final consumers. The value of direct farm sales per capita is defined as the dollar value of direct farm sales in the county divided by the population of the county. The density of farmers' markets is defined as the number in the county per 1,000 county residents. A farmers' market is defined as an establishment in which at least two vendors retail food products directly to the consumer through the same venue. In order to count as a farmers' market, more than half of total retail sales must be obtained from the consumer directly. Lastly, farm-to-school programs consist of special programs designed to bring agricultural products directly from the farm to local schools for consumption. Such programs include direct sourcing from local producers, local sourcing through the Department of Defense procurement system (known as "DOD Fresh"), school gardens, farm tours, farm-related nutrition education or other classroom activities, and school menus highlighting locally-sourced foods. An indicator variable is included if the county has a farm-to-school program (=1) or does not (=0). A county is counted as having a farm-to-school program whether the program covers the whole county or whether the program operates only in a school or school district within the county.

Other variables capture aspects of the built environment relating to food accessibility, physical activity, and geography. Food accessibility is indicated by the percentage of housing units in a county that are more than one mile from a supermarket or large grocery store and have no car, and also by the percentage of the total population in a county that is low income and lives more than one mile from a supermarket or large grocery store. Physical activity is indicated by the density of recreational & fitness facilities, measured as the number of fitness and recreation centers in a county divided by the number of county residents. Fitness and recreation centers are defined as facilities primarily engaged in activities such as exercise or recreational sports activities. The geographic environment is indicated by a natural amenity index based on topographical variation (e.g., water, mountains, sunny weather patterns, etc.). The index measures a county's natural amenities score as a standard deviation from the all-county average value. An index with a large negative value indicates a county that has a much lower score than the all-county average, while a large positive value indicates a county with natural amenities higher than the all-county average. An indicator is also included if the county is a metropolitan (=1) or non-metropolitan county (=0). Under the 2003 Office of Management and Budget (OMB) classification, counties are classified as metropolitan if they are economically tied to the central counties, as measured by the share of workers commuting on a daily basis to the central counties. Counties are classified as non-metropolitan if they are outside the boundaries of metropolitan areas and have no cities with 50,000 residents or more.

Socioeconomic variables are also included. The racial/ethnic composition of the county is measured by indicators for the percent of county residents that are white, that are black or African-American, and that are Asian. Economic well-being is indicated by median household income (in thousands of U.S. dollars). Lastly, the poverty rate indicates the percent of county residents with household income below the poverty threshold.

4. Results and Discussion

The data are first investigated for normality. Several test statistics substantiate the rejection of normality, which are summarized in table 2. Each test has its own advantages and disadvantages. For example, the Jarque-Bera test and the Lilliefors test are sensitive to small samples. The Shapiro-Wilks test and the Anderson-Darling test are considered best, in terms of power, for detecting departures from normality. Regardless of the test statistic, each rejects the normality hypothesis (although rejection of normality is stronger in the obesity model). Therefore, OLS is unsuitable and robust regression is more appropriate. The MM-estimator is applied next to assess the impact of the built environment on the prevalence of obesity and diabetes. Parameter estimates are given in table 3. Figure 1 and Figure 2 display the final weights used for each observation in the MM-estimator regression for obesity and diabetes, respectively, indicating a non-trivial number of observations are down-weighted.

Socioeconomic indicators perform as expected and are similar to other studies on obesity, though fewer comparisons for diabetes are available (Boardman et al. 2005; Lopez 2007; Vandegrift and Yoked 2004). The percentage of the population white or black exerts a positive influence on both obesity and diabetes, while the percentage Asian exerts a negative influence (the percent Asian is insignificant for diabetes). A one percentage point increase in the percentage of blacks increases the obesity rate by 0.09% and the diabetes rate by 0.06%. Rising median household income is associated with reduced rates of obesity and diabetes. An additional $1000 in median county income reduces rates of obesity and diabetes by about 0.05%. A negative association between income and obesity is also a common finding (Lopez 2007; Vandegrift and Yoked 2004). While the poverty rate does not seem to be associated with diabetes, an increase in the poverty rate is associated with a higher obesity rate. While most studies in the literature do not decompose the impacts of income and poverty, Chen et al. (2010) find that individuals living in low-income communities with income less than 200% of the federal poverty level tended to have higher BMIs.

Results regarding food accessibility indicate that distance and availability play important roles in both obesity and diabetes, particularly for low-income households. A one percentage point increase in the percentage of residents with no car and more than 1 mile to a supermarket or grocery store increases the diabetes rate by 0.10% but does not influence obesity. A one percentage point increase in the percent of low-income households greater than one mile to a supermarket or grocery store increases both the obesity and diabetes rates by 0.03%. Many studies find that low-income households live further away from healthy food outlets and closer to unhealthy places, like fast-food restaurants (Block et al. 2004; Moore and Diez Roux 2006; Powell et al. 2007). Lack of access to healthier foods and easier accessibility of processed and unhealthy foods can cause decreased consumption of fresh fruits and vegetables among the poor (Morland et al. 2002).

Density of recreational and fitness facilities has a strong negative association. For every additional fitness facility per 1,000 people, the diabetes rate falls by 0.57% while the obesity rate falls by 3.06%. Studies find that access to such facilities is associated with greater physical activity (Brownson 2001; Poortinga 2006) and better health (Mobley et al. 2006). Counties that have more natural amenities also have lower rates of obesity and diabetes. The amenity index is likely a proxy for the extent of outdoor activities available and may reflect the degree of residents' physical activity. Results suggest that more open space can lead to lower rates of obesity and diabetes, a finding consistent with other studies (Ellaway et al. 2005; Giles-Corti 2005).

Being a metropolitan county is also significantly and positively associated with higher rates of obesity and diabetes. This may reflect the influence of urban sprawl (Ewing et al. 2003; Eid et al. 2008; Zhao and Kaestner 2010). Metropolitan counties are larger population-wise and have a more urban infrastructure. More time is spent traveling in vehicles and less time spent walking, which could lead to greater rates of obesity (Lopez-Zetina 2006). Although the existing evidence in the literature is mixed, results here lend support to the urban sprawl and obesity hypothesis.

While the density of fast-food restaurants is associated with higher rates of diabetes, the effect on obesity is not significant. Although there is evidence that consumption of fast-food is associated with obesity and insulin resistance (Jeffrey and French 1998; Pereira et al. 2005), there is conflicting evidence that the actual density of fast-food outlets is positively correlated with obesity (Feng et al. 2010). For example, Maddock (2004) finds a positive correlation between prevalence of fast-food outlets and obesity using state-level data, a finding confirmed by Mehta and Chang (2008) and Chou et al. (2004) using individual-level data. Jeffery et al. (2006), however, find that while eating at fast-food restaurants is positively associated with obesity, the actual density of fast-food outlets is not.

Full-service restaurants have a significant and negative influence on both obesity and diabetes. An additional full-service restaurant per 1,000 people decreases the diabetes rate by 0.58% and the obesity rate by 1.22%. The strong negative association of full-service restaurant density with obesity and diabetes confirms the finding in Mehta and Chang (2008). The density of full-service restaurants may indicate an eating environment with better food options or may proxy attitudes of residents with preferences for healthier foods.

The density of grocery and supermarket stores is not significantly associated with obesity or diabetes. The insignificant effect obtained here may be the result of combining supermarkets and small-end grocery stores in the same measure which can have opposing effects. Morland and Evenson (2009) find that areas with more small grocery stores had higher obesity prevalence. While Morland et al. (2006) find a negative association for supermarkets and a positive association for grocery stores, once the model included socioeconomic variables the positive effect became insignificant. The insignificant estimate could also be the result of including such a complete set of environmental measures. Others find the density of grocery stores to be unrelated to obesity once a full set of environmental indicators is included (Mobley et al. 2006).

The density of gas-based and no-gas convenience stores is not associated with higher rates of obesity and but is associated with greater prevalence of diabetes. Every additional no-gas convenience store per 1,000 people increases the diabetes rate by 2.04%. Other studies find a positive association between convenience stores and obesity, however, these studies tend not to include distinct measures of convenience stores based on the availability of gas (Morland and Evenson (2009) is one exception). Results suggest that no-gas convenience stores have a greater negative impact on health. While selling food is not the only business of gas-based convenience stores, the business of no-gas convenience stores usually depends solely on selling food items, which tend to be unhealthy processed foods.

Supercenter density has a strong influence on obesity. Every additional supercenter per 1,000 people increases the obesity rate by 8.95%, which suggests they play a pivotal role in influencing obesity. Supercenters and club stores advertise on the basis of substantial savings, often using quantity discounts to promote bulk purchasing. Moreover, such business venues tend not to offer foods like fresh fruits and vegetables, but instead primarily sell processed foods that have longer shelf-life (Bustillos et al. 2009). While none of the existing studies on the built environment and obesity have examined the differential impact of supercenters from other retail food outlets, the results here support the finding in

Courtemanche and Carden (2010) who find the density of Wal-Mart supercenters is positively associated with higher rates of obesity.

Finally, measures describing the 'local' food economy are noteworthy. The percentage of farms in a county that engage in direct sales has a significant and negative association with the obesity rate. For every $100 increase in per capita direct farm sales, the obesity rate falls by 0.90% and the diabetes rate falls by 1.2%. The density of farmers' markets also influences diabetes prevalence. Every additional farmers' market per 1,000 people decreases the diabetes rate by 0.73%. Although no study has looked at the impact of the 'local' food economy and obesity directly, existing research finds improved access to farmers' markets is associated with increased availability of affordable healthy food (Larsen and Gilliland 2009) and increased consumption of fresh fruits and vegetables among low-income people (Conrey et al. 2003). The presence of a farm-to-school program is negatively associated with obesity and diabetes. Counties with a farm-to-school program have on average a 1.09% lower obesity rate and 0.27% lower diabetes rate. Children attending schools with such programs tend to drink less sugary beverages and eat less energy-dense, low-nutrient foods (Briefel et al. 2009).

5. Policy Implications and Conclusions

This study investigates the influence of the built environment on both obesity and diabetes with a full range of environmental measures, including measures relating to the 'local' food economy. Few studies include a complete model of environmental determinants of obesity or diabetes and instead focus on particular environmental factors in isolation such as fast-food restaurants, grocery stores, or physical activity. The estimated effects of environmental indicators on health outcomes obtained in isolation can result in under- or over-estimated relationships (Black and Macinko 2008), which emphasizes the importance of comprehensive studies. Moreover, a robust regression estimator is used to account for non-normality of the data and to accommodate outliers. Several policy implications emerge from the results in this paper.

First, while few studies include a measure of poverty, the positive association found here confirms the conclusion in Drewnowski (2004) that obesity follows a socioeconomic gradient, with higher rates found among the poor. This suggests that although community-level interventions should aim to benefit all members, special attention should be given to the poor, particularly minorities, who are at greater risk. Second, results on the access measures emphasize that community-level interventions should target low-income households. Moreover, results suggest that effective interventions may involve improving accessibility of healthy food through transportation strategies. This may include better public transit programs with improved access to food retailers, enhanced food delivery services by supermarkets, or even pick-up and drop-off services for customers offered by the stores themselves (Mikkelsen and Chehimi 2007). Third, since geographic amenities and physical activity are such strong negative determinants of obesity, results imply that community-level interventions should include efforts to expand the availability of facilities that promote physical activity and the creation of more parks and open space, particularly in metropolitan counties.

Finally, results suggest a set of interventions available to regional planners and public health professionals in the form of the 'local' food economy. Rather than respond to a growing obesity epidemic and an alarming diabetes rate with narrowly focused attempts to reduce access to unhealthy foods, results demonstrate effective community-level interventions can also involve strengthening the 'local' food economy. This requires urban and rural planners to incorporate the 'local' food market in community design policies, which will help public health practitioners to utilize 'local' foods to influence dietary health. The planning and building of a 'local' food system infrastructure has been largely ignored by urban planners as well as public health managers (Nichol, 2003). Action towards facilitating growth and expansion of the ‘local’ food market is warranted given the potential for combating obesity and diabetes. Specific strategies involve increasing the number of farms that sell directly to the consumer, augmenting direct farm sales through marketing campaigns, and enhancing farm-to-school programs. Such strategies may bring healthy food options not just to the community at-large, but also to low-income and high-risk people.

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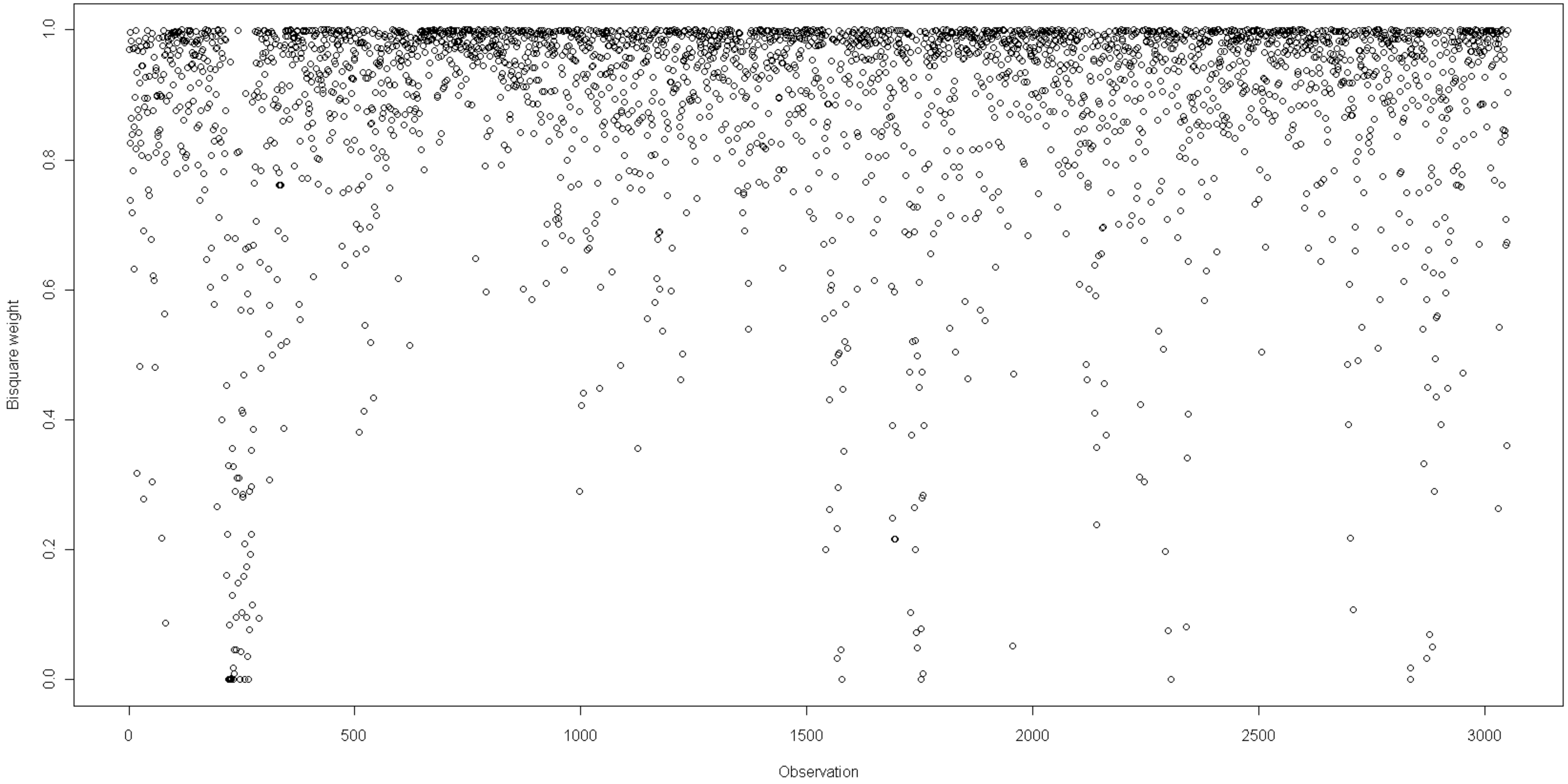

Figure 1. Final weights from obesity MM-estimator

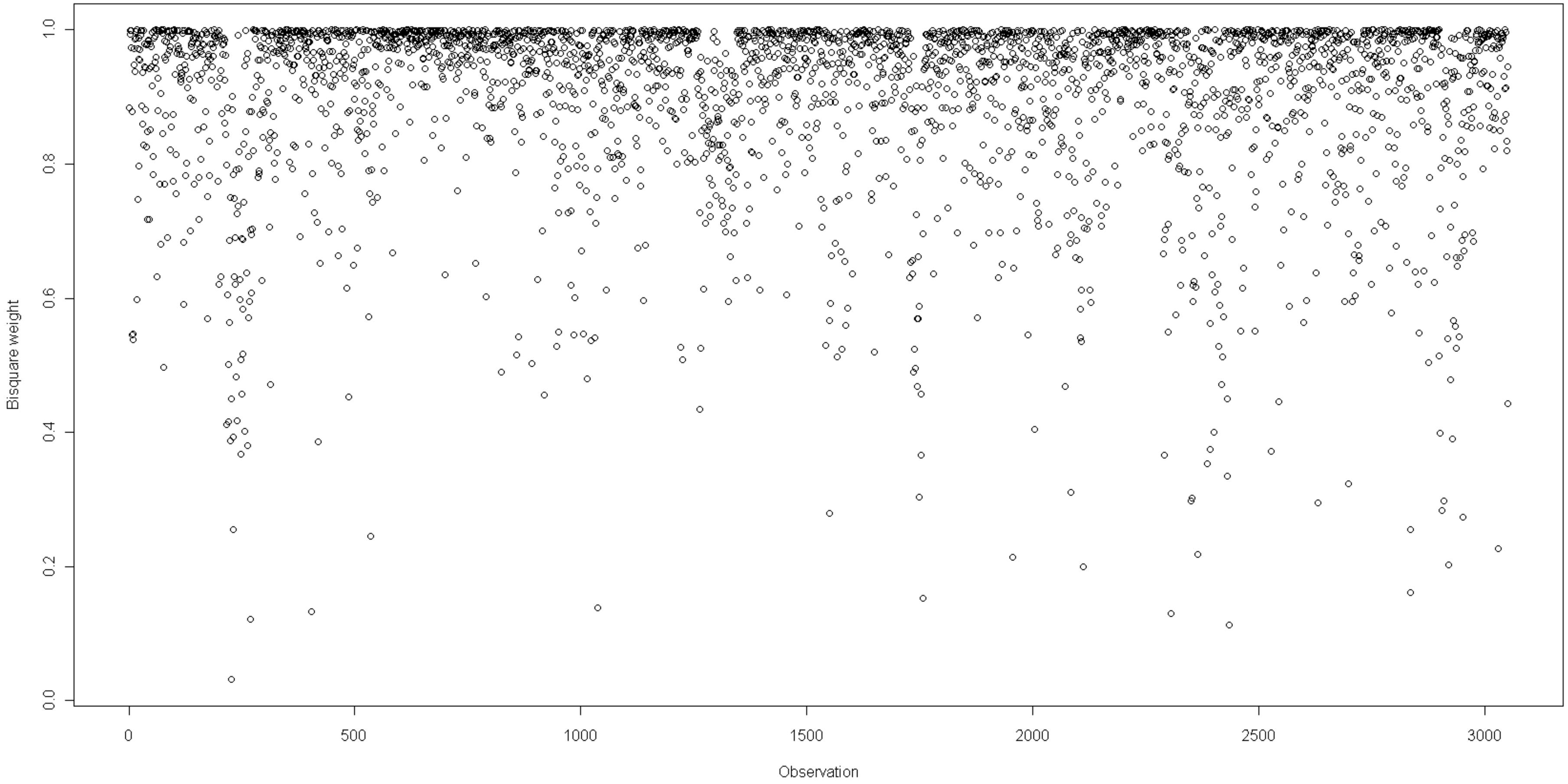

Figure 2. Final weights from diabetes MM-estimator

Table 1. Data Description

Variable	Year	Source	Mean	SD	Min	Max
Adult obesity rate	2007	CDC/BRFSS	28.28	3.61	12.5	43.50
Adult diabetes rate	2007	CDC/BRFSS	9.65	2.01	3.20	17.40
Fast-food restaurants density	2007	Census Bureau	0.59	0.32	0	7.12
Full-service restaurants density	2007	Census Bureau	0.81	0.59	0	14.24
Supermarkets-Grocery store density	2007	Census Bureau	0.28	0.22	0	3.27
Convenience stores no gas density	2007	Census Bureau	0.08	0.10	0	1.71
Convenience stores with gas density	2007	Census Bureau	0.56	0.31	0	4.78
Supercenters and club stores density	2007	Census Bureau	0.01	0.02	0	0.26
Percent of farms with direct sales	2007	Agricultural Census	6.34	5.96	0	100
Direct farm sales per-capita (dollars)	2007	Agricultural Census & Census Bureau	7.30	12.69	0	274.51
Farmers' market density	2008	ERS & Census Bureau	0.04	0.07	0	1.01
Farm-to-school program	2009	Farm-to-school Network	0.06	0.24	0	1
Percent residents no car and >1 mile to store	2006	Multiple sources*	3.98	2.60	0	27.91
Percent low income and >1 mile to store	2006	Multiple sources*	22.81	11.37	0	79.49
Recreational/fitness facilities density	2007	Census Bureau	0.09	0.09	0	1.19
Natural amenity index	1999	ERS	3.49	1.04	1	7.00
Metropolitan/non-metropolitan county	2000	ERS	0.35	0.48	0	1.00
Percentage white	2008	Census Bureau	79.54	19.04	2	99.40
Percentage black	2008	Census Bureau	9.00	14.32	0	85.50
Percentage Asian	2008	Census Bureau	0.98	1.89	0	30.90
Median household income (dollars)	2008	Census Bureau	44034	11376	19182	111582
Poverty rate	2008	Census Bureau	15.27	6.05	3.10	54.40

* Data are sourced from "Access to Affordable and Nutritious Food -- Measuring and Understanding Food Deserts and Their Consequences: Report to Congress." See the ERS Food Atlas documentation for more information (http://www.ers.usda.gov/foodatlas/).

Table 2. Normality test statistics (p-value in parentheses)

Test name	Critical value[1]	Obesity model	Diabetes model
Anderson-Darling	0.751	9.135	1.953
Cramer-von Mises	0.220	1.281	0.322
Lilliefors	0.016	0.042	0.021
Jarque-Bera	5.99	364.002	22.565
Shapiro-Wilks[2]	1.00	0.983	0.998

[1] The critical value is based on a 5% significance level.
[2] Rejection occurs if the test statistic is less than the critical value.

Table 3. Robust regression estimates (t-statistics in parentheses)

Variable	Obesity	Diabetes
Intercept	30.189***	9.468***
	(34.846)	(17.348)
Percentage white	0.024***	0.017***
	(5.402)	(5.983)
Percentage black	0.093***	0.064***
	(16.078)	(20.865)
Percentage Asian	-0.174***	-0.016
	(-5.339)	(-0.668)
Median household income (thousands of dollars)	-0.440***	-0.525***
	(4.540)	(-9.318)
Poverty rate	0.060***	-0.011
	(3.225)	(-0.955)
Percent of households no car and >1 mile to store	0.026	0.101***
	(0.786)	(3.936)
Percent low income and >1 mile to store	0.025***	0.027***
	(2.975)	(4.650)
Recreational and fitness facilities density	-3.062***	-0.565
	(-5.050)	(-1.629)
ERS natural amenity index	-0.752***	-0.054*
	(-12.433)	(-1.795)
Metropolitan/non-metropolitan counties	0.289***	0.245***
	(2.641)	(3.796)
Fast-food restaurants density	-0.304	0.323***
	(-1.500)	(2.676)
Full-service restaurants density	-1.222***	-0.578***
	(-9.643)	(-8.394)
Supermarkets-Grocery store density	-0.226	0.029
	(-1.016)	(0.243)
Convenience stores no gas density	0.124	2.037***
	(0.276)	(6.342)
Convenience stores with gas density	0.257	0.239**
	(1.448)	(2.202)
Supercenters and club stores density	8.948***	1.700
	(3.321)	(1.348)
Percent of farms with direct sales	-0.027***	-0.007
	(-3.430)	(-1.388)
Direct farm sales per capita (dollars)	-0.009***	-0.012***
	(-2.656)	(-5.238)
Farmers' market density	0.143	-0.729**
	(0.245)	(-1.986)
Farm-to-school program	-1.093***	-0.266***
	(-5.913)	(-2.640)

*** indicates two-tailed significance at the 1% level, ** at the 5% level, and * the at 10% level.