Poverty, Sprawl, and Restaurant Types Influence Body Mass Index of Residents in California Counties

Jennifer Gregson, PhD, MPH[a]

ABSTRACT

Objectives. This article examines the relationships between structural poverty (the proportion of people in a county living at ≤130% of the federal poverty level [FPL]), urban sprawl, and three types of restaurants (grouped as fast food, chain full service, and independent full service) in explaining body mass index (BMI) of individuals.

Methods. Relationships were tested with two-tiered hierarchical models. Individual-level data, including the outcome variable of calculated BMI, were from the 2005, 2006, and 2007 California Behavioral Risk Factor Surveillance Survey (n=14,205). County-level data (n=33) were compiled from three sources. The 2000 U.S. Census provided the proportion of county residents living at ≤130% of FPL and county demographic descriptors. The sprawl index used came from the Smart Growth America Project. Fast-food, full-service chain, and full-service independently owned restaurants as proportions of the total retail food environment were constructed from a commercially available market research database from 2004.

Results. In the analysis, county-level demographic characteristics lost significance and poverty had a consistent, robust association on BMI ($p<0.001$). Sprawl demonstrated an additional, complementary association to county poverty ($p<0.001$). Independent restaurants had a large, negative association to BMI ($p<0.001$). The coefficients for chain and fast-food restaurants were large and positive ($p\leq0.001$), indicating that as the proportion of these restaurants in a county increases, so does BMI.

Conclusions. This study demonstrates the important role of county poverty and urban sprawl toward understanding environmental influences on BMI. Using three categories of restaurants demonstrates different associations of full-service chain and independent restaurants, which are often combined in other research.

[a]University of California, Davis, Department of Sociology, Davis, CA (current affiliation: California Department of Public Health, Network for a Healthy California, Sacramento, CA)

Address correspondence to: Jennifer Gregson, PhD, MPH, California Department of Public Health, Policy, Planning, and Evaluation Section, PO Box 997377, MS 7204, Sacramento, CA 95899-7377; tel. 916-449-5455; fax 916-449-5414; e-mail <Jennifer.gregson@cdph.ca.gov>.

©2011 Association of Schools of Public Health

Structural arguments to explain the prevalence of population overweight often focus on the food environment, such as retail stores where grocery items are purchased and, to a lesser degree, restaurants where prepared food is purchased.[1] However, restaurants and the food environment are only part of an environmental-level, structural explanation. Population overweight has increased for all population segments, but rates in lower-income groups are disproportionately higher,[2] likely indicating that disadvantage from poverty is a contributing factor. Urban sprawl has also been empirically linked to weight status of the people living in sprawling areas.[3] This article aims to untangle the relationships between county poverty, urban sprawl, and three types of restaurants toward explaining body mass index (BMI), and to assess the contributions of each of the three factors. It examines these factors in the 33 most populous of California's 58 counties, which accounts for 97% of the state's population.

BACKGROUND

Presence of restaurants

Although restaurants are a large part of the built food environment, they are far less studied as part of a structural explanation for BMI than the retail components of the food environment. There is plausible theoretical argument that restaurant food is higher in fat and calories than foods prepared at home,[4] and, thus, it may contribute to weight gain. Research on restaurants typically distinguishes between fast-food and full-service establishments. Results linking the presence of both varieties to population BMI are mixed, but more conclusive for fast food.

The association between eating fast food and weight gain among individuals is consistently found in the literature, as concluded by Larson et al.,[1] thereby establishing a link between individual consumption behavior and BMI. The structural argument about the *presence* of fast food as a component of the food environment and the influence on individuals is far less clear. Structural or environmental-level studies of smaller geographic areas such as census tracts or blocks do not generally detect significant relationships between the presence of fast-food stores and BMI of the residents.[5,6] However, national studies of fast food grouped at the county level[7] and between states[8] are able to detect population-wide patterns.

Structural relationships between obesity and the presence of full-service restaurants are more ambiguous, and one study actually found an inverse relationship between the presence of full-service restaurants and BMI.[7] Three other studies demonstrated no relationship to full-service restaurants,[9–11] though only one of these was conducted with adults.[11] This body of research is limited because there are few studies, and the knowledge base is emerging. However, this research is also limited by possible measurement issues, because chain restaurants that are full service are not distinguished from independently owned restaurants. Grouping these types of restaurants together assumes that they are similar. But anecdotally, there is little reason to assume that chain restaurants and independent restaurants are similar. Chain restaurants have a corporate organizational structure and, as such, have more purchasing power; they aim for consistency in their food and standardize preparation in company manuals, using approved vendors chain-wide, and, in some cases, in off-site preparation kitchens; and they have more political and legal resources for land use and store placement than an independent restaurant. Independently owned restaurants are small businesses and have more autonomy to respond to customer requests and employ locally based marketing practices. It should not be assumed that restaurant chains have the same theoretical and empirical relationships as independently owned restaurants to BMI. There is a dearth of theoretical and empirical distinctions between these types of restaurants in the food environment literature; one intent of this study was to determine if chain and independent restaurants indeed have a different relationship to BMI.

A conclusive relationship between full-service restaurant presence in general and BMI has not been consistently demonstrated in past research and may continue to evolve as methods and definitions, such as separate categories for independent restaurants, continue to emerge. Furthermore, from the perspective of a structural argument, the type and placement of restaurants may also be influenced by other structural factors, county poverty, and urban sprawl.

County poverty

Poverty is more than just an individual's economic status. When experienced by large numbers of people, poverty is a social condition and has social processes embedded within it, such as residential segregation. Structural poverty may well contribute to social and physical environments that exacerbate obesity. Kreiger argued that including poverty is an essential component of understanding disease etiology in general, and that "economic deprivation is present, and it matters."[12] She further maintained that the poor have worse health because of social injustice, and not because the poor are deficient in some way or because poor health interferes with gaining economic prosperity.

A review of income inequality (when a small percent of the population owns a disproportionately large amount of the resources) and health found that in 70% of the studies, when a society has a high degree of income inequality, that society has worse population health.[13] Areas with higher inequality do not have worse health outcomes simply because there are more poor people.[13] County poverty is more than the aggregation of people with low incomes. Rather, the processes of social selection and the sorting of people inherent in residential income segregation,[14] and the ensuing concentration of poverty, can influence the amount of resources in a community and the quality and types of businesses choosing to be located there. When the poor are segregated from the wealthy into specific areas, segregating the poor can contribute to conditions that result in higher BMI.

The process of separating rich from poor in residential settlement is deliberate, evidenced by residential zoning policies intended to maintain property values of single-family homes,[15] and placement of food stores follows residential settlement patterns.[16] Using the degree of county poverty as an explanation of the food environment addresses a structural approach and frames it in terms of privilege and disadvantage. However, structural poverty has rarely been considered with the presence of restaurants or other environmental explanations, such as sprawling urban form.

Sprawl and physical activity in the environment

Sprawl and land use are increasingly being identified as a cause of health problems.[15,17] The report "Measuring the Health Effects of Sprawl"[3] demonstrated that county-level sprawl was associated with higher BMI, less walking, and higher risk of hypertension. The premise of sprawl as a contributing factor to BMI is that activity structured into daily life in a traditional city form, such as walking or biking for errands and commuting (utilitarian physical activity, as opposed to leisure-time physical activity), is being minimized by environmental forces that emphasize sprawling urban form and automobile dependence,[15,18] resulting in weight gain.

Sprawl was included in this analysis to control for effects of utilitarian physical activity that may influence BMI, and also to control for sprawl itself, which may be related to restaurant presence or county poverty. Studies examining store and restaurant placement generally do not account for the effects of sprawl; they are treated as two separate research topics. In two recent comprehensive literature reviews about BMI and eating environments, which dedicated a significant amount of discussion to environmental factors, none of the articles accounted for sprawl,[1,19] despite sprawl's empirical association with BMI. Thus, testing the relationships of restaurants in the built food environment to BMI should adjust for county poverty to reflect disadvantage in restaurant placement decisions and should adjust for sprawl to control for physical activity and restaurant placement associated with sprawling areas.

METHODS

The goal of this analysis was to create a model for each type of restaurant to clarify the relationship between a restaurant type and BMI, as well as to account for relationships with county poverty and sprawl. This research question had a nested structure; it addressed individual behaviors (BMI) that exist within and are influenced by a larger, constructed environment (county poverty, sprawl, and proportional presence of restaurants). Two-tiered hierarchical models were employed. At each level, the model demonstrated the relationship of variables within a level and how variables in a more specific level (e.g., individuals or, more generally, level-1) are influenced by variables in other broader levels (e.g., environment and, more generally, level-2). The analytical approach focuses the statistical explanation on the main effects of the environmental variables on individuals. In this study, the data were from individuals in California counties; thus, the datasets were geographically linked by county. County-level measures of poverty, sprawl, and restaurant types were regressed on individual-level measures of demographic characteristics and BMI.

Individual data were from the 2005, 2006, and 2007 California Behavioral Risk Factor Surveillance System (BRFSS)[20] (n=14,205, Table 1) and included BMI as the outcome variable and basic sampling characteristics of the respondents. The data were weighted using the BRFSS sampling weights, modeling other similarly structured studies,[7,21,22] and the weights were normalized. BMI has many accepted influential factors and correlations with individual characteristics. Increased BMI is associated with age, gender, race, and income in individuals in surveillance surveys;[23] thus, these variables are used for the individual-level model. Each respondent can be identified by the county of residence, making it possible to link micro-level data with macro-level data.

The county dataset was compiled from multiple sources. The 2000 U.S. Census provided demographic data, used as control variables, and the proportion of the population living at ≤130% of the federal poverty line (FPL) as a measure of income inequality. This is the line of demarcation that the federal government

Table 1. Characteristics of BRFSS respondents and California counties, of counties included in analysis of influence of poverty, sprawl, and restaurant type on BMI

	Individual data (n=14,205), unweighted			
Characteristic	*Mean*	*SD*	*Minimum*	*Maximum*
BMI	26.90	5.58	9.30	71.00
Age	50.38	16.88	18.00	98.00
Gender				
Female	0.60	0.51	0.00	1.00
Male	0.40	0.49	0.00	1.00
Race/ethnicity				
White	0.65	0.48	0.00	1.00
Black	0.04	0.21	0.00	1.00
Hispanic	0.23	0.42	0.00	1.00
Other (ref.)	0.08	0.27	0.00	1.00
Annual income				
<$15,000	0.14	0.35	0.00	1.00
$15,000–$49,999	0.36	0.48	0.00	1.00
≥$50,000 (ref.)	0.50	0.50	0.00	1.00
	County data (n=33)			
Characteristic	*Mean*	*SD*	*Minimum*	*Maximum*
Sprawl index	0.00	1.00	−1.15	4.35
Proportion living at ≤130% of federal poverty level	0.19	0.08	0.09	0.34
Proportion Hispanic	0.29	0.16	0.06	0.78
Proportion white	0.57	0.17	0.22	0.88
Proportion black	0.05	0.04	0.00	0.15
Proportion Asian (ref.)	0.08	0.07	0.02	0.31
Proportion male	0.50	0.02	0.49	0.57
Proportion aged ≥45 years	0.45	0.05	0.34	0.55
Proportion aged 18–44 years (ref.)	0.55	0.05	0.45	0.66
Proportion fast-food restaurants	0.18	0.04	0.06	0.25
Proportion independently owned restaurants	0.42	0.07	0.27	0.61
Proportion chain restaurants	0.04	0.01	0.02	0.07

BRFSS = Behavioral Risk Factor Surveillance System

BMI = body mass index

SD = standard deviation

ref. = reference

uses for Food Stamp eligibility, free school lunch eligibility, and other safety-net programs.

County-level data on restaurants were from the commercial market research database of Dun & Bradstreet[24] that includes a comprehensive listing of all California food retail establishments. Restaurants are categorized by fast food, chains with six or more that are not fast food, and independently operated restaurants that are not fast food. These restaurant variables are presented as proportions of the total retail food outlets in the county. The denominator was created by summing the total count of supermarkets (large chains), grocery stores (small and independent chains), fast food, convenience stores, chain restaurants, independent restaurants, fruit and vegetable markets, delis, independent and chain coffee stores, bakeries, other single-item vendors such as butcher shops, co-ops, commissaries, ice cream stores, and all other food stores.

The sprawl index was provided by the Smart Growth America Study.[3,25] The index was constructed so that more compact areas would have a larger index and more sprawling areas would have a smaller index. California data were extracted from the national dataset and ranked on a national scale. An index comprised only of California counties would change the score, but not the order in which counties are ranked. However, the sprawl index required some measures that were not available for the least populated counties; these counties did not have an index score and were not included in the analysis. The Figure shows a list of all the included and excluded counties. The 33 included counties accounted for 97% of the state's population.

The models were built in an iterative process, first including demographic control variables (which became nonsignificant) and then introducing predictor variables representing components of the posed research question. Final models included only significant predictor variables. Multicollinearity between the county-level variables in the model was tested using the variance inflation factor (Table 2), for which scores greater than 10 are considered high. County poverty was introduced first, as a theoretically pervasive explanatory variable for BMI. Sprawl was then introduced to adjust for relationships between what is theorized to be utilitarian physical activity and BMI.[3,26] Each restaurant type, in no particular order, was then included in a model, adjusting for county poverty and sprawl, and thereby demonstrating the contributions of each predictor to a relationship with BMI. In all models, the individual-level variables remained the same. The analysis was conducted with HLM version 6.06.[27] Individual variables were group centered, and county-level predictor variables were grand-mean centered.

RESULTS

A significant null model indicated that there was adequate variance among counties to test multilevel models. The grand mean for BMI in California from

Figure. California counties excluded and included from the analysis of the influence of poverty, sprawl, and restaurant type on body mass index

Excluded	*Included*
Alpine	Alameda
Amador	Butte
Calaveras	Contra Costa
Colusa	El Dorado
Del Norte	Fresno
Glenn	Imperial
Humboldt	Kern
Inyo	Kings
Lake	Los Angeles
Lassen	Marin
Madera	Merced
Mariposa	Monterey
Mendocino	Napa
Modoc	Orange
Mono	Placer
Nevada	Riverside
Plumas	Sacramento
San Benito	San Bernardino
Sierra	San Diego
Siskiyou	San Francisco
Sutter	San Joaquin
Tehama	San Luis Obispo
Trinity	San Mateo
Tuolumne	Santa Barbara
Yuba	Santa Clara
	Santa Cruz
	Shasta
	Solano
	Sonoma
	Stanislaus
	Tulare
	Ventura
	Yolo

2005–2007 was 26.909, with a standard error (SE) of 0.184. The 95% confidence interval for the mean of county means for BMI for the 33 counties was between 26.548 and 27.270. BMI is defined as "normal" at 18.5–24.9, "overweight" at 25.0–29.9, and "obese" at ≥30.0.[28] The variance of the county means around the grand mean (mean of county means) is 1.032. To gauge the magnitude of the variation among counties for BMI, a plausible values range was calculated with a 95% probability, yielding a range of 25.898 to 27.920. The Chi-square test for the null model shows the test has a value of 352.023 with 32 degrees of freedom and $p<0.001$, indicating that significant variation does exist among counties in the BMI of residents. The interclass correlation was used to calculate the specific amount of variance in BMI between counties. The total amount of county-level variance that can be explained is 3.43%.

Table 2. Testing for multicollinearity between environmental-level predictor variables using the VIF in an analysis of the influence of poverty, sprawl, and restaurant type on body mass index of residents in 33 California counties

	VIF in model		
Variable	*Final model 4*	*Final model 5*	*Final model 6*
County poverty	1.177	1.357	1.578
Sprawl	1.182	1.178	1.532
Chain restaurants	1.097	NA[a]	NA[a]
Fast-food restaurants	NA[a]	1.398	NA[a]
Independent restaurants	NA[a]	NA[a]	2.171

[a]Not all variable conbinations were tested.

VIF = variance inflation factor

NA = not applicable

Control variables

The analysis first demonstrated variation in socioeconomic characteristics of people and the counties in which they live and how these influence BMI. Individual variables typically associated with BMI and county demographic variables were included in this base model, and it served as the foundation for future model iterations. Poverty, sprawl, and stores were added to the level-2 models in ensuing iterations, and nonsignificant level-2 variables from preceding models were dropped. The level-1 model was unchanged through the analysis because these variables are standard epidemiologic controls.

Table 3 describes the individual- and county-level associations with BMI. County-level demographic variables for race/ethnicity were statistically significant, while those for gender and age were not (Table 3, Model 1). All individual variables were statistically significant except for annual income <\$15,000. Individual data were expected to be highly significant because there is a genetic component to BMI, as with many health outcomes, and because the behaviors that affect BMI—eating and exercise—are individual actions. Recall, though, that the proposed analysis focused on the role of the county-level variance. In all, county demographics and individual demographics explained slightly more than a third (39%) of the level-2 variance, indicating a partial explanation. But with nearly 60% of the level-2 variance unexplained, there remains room for additional theories about what influences BMI.

County poverty

The next iteration of models tested county poverty. When county poverty was tested with race/ethnicity variables, two of the three lost significance, and so the

Table 3. County poverty and sprawl, as well as proportions of independent, chain, and fast-food restaurants in a county, predict body mass index of individuals in an analysis of 33 California counties

	Model 1: Base			*Model 2: County poverty, reduced*			*Model 3: County poverty and sprawl*			*Model 4: County poverty, sprawl, and chain restaurants*			*Model 5: County poverty, sprawl, and fast-food restaurants*			*Model 6: County poverty, sprawl, and independently owned restaurants*		
	Coeff.	*P-value*	*SE*	*Coeff.*	*P-value*	*SE*	*Coeff.*	*P-value*	*SE*	*Coeff.*	*P-value*	*SE*	*Coeff.*	*P-value*	*SE*	*Coeff.*	*P-value*	*SE*
County-level predictors (fixed effects)																		
Intercept	27.067	<0.001	0.133	27.036	<0.001	0.128	27.036	<0.001	0.128	27.043	<0.001	0.111	27.036	<0.001	0.101	27.052	<0.001	0.091
Proportion ≤130% FPL				8.343	<0.001	2.268	8.941	<0.001	2.329	7.845	<0.001	1.910	5.835	<0.01	1.850	4.127	<0.05	2.003
Sprawl							−0.013	<0.001	0.004	−0.014	<0.01	0.004	−0.010	<0.05	0.005	NS		NS
Proportion chain restaurants										21.337	<0.05	9.396						
Proportion fast-food restaurants													8.620	<0.01	2.872			
Proportion independently owned restaurants																−8.254	<0.001	1.557
Proportion																		
Hispanic	7.805	<0.001	1.395	[a]														
White	5.375	<0.01	1.785	[a]														
Black	9.907	<0.01	3.576	[a]														
Male	NS		NS															
Aged ≥45 years	NS		NS															
Individual predictors (fixed effects)																		
Age	0.034	<0.001	0.004	0.034	<0.001	0.004	0.034	<0.001	0.004	0.034	<0.001	0.004	0.034	<0.001	0.004	0.034	<0.001	0.004
Male	0.929	<0.001	0.122	0.927	<0.001	0.122	0.929	<0.001	0.122	0.926	<0.001	0.122	0.926	<0.001	0.122	0.928	<0.001	0.122
Race/ethnicity																		
White	1.697	<0.001	0.223	1.701	<0.001	0.223	1.664	<0.001	0.228	1.698	<0.001	0.223	1.699	<0.001	0.223	1.700	<0.001	0.222
Black	3.314	<0.001	0.382	3.319	<0.001	0.382	3.293	<0.001	0.386	3.316	<0.001	0.381	3.313	<0.001	0.382	3.315	<0.001	0.382
Hispanic	2.983	<0.001	0.470	2.983	<0.001	0.469	2.957	<0.001	0.474	2.980	<0.001	0.470	2.987	<0.001	0.468	2.981	<0.001	0.469
Other (reference)																		
Annual income																		
<$15,000	NS		NS	NS		NS	NS		NS	NS		NS	NS		NS	NS		NS
$15,000–$49,999	0.424	<0.05	0.178	0.425	<0.05	0.178	0.425	<0.05	0.178	0.426	<0.05	0.178	0.426	<0.05	0.178	0.426	<0.05	0.178
≥$50,000 (reference)																		
Model fit																		
Variance component, level-2	0.633			0.544			0.437			0.297			0.243			0.261		
Percent of level-2 variance explained	38.7			47.3			57.7			71.2			76.4			74.7		
Chi-square	229.889	<0.001		238.094	<0.001		127.127	<0.001		113.911	<0.001		100.221	<0.001		101.872	<0.001	

[a]Two of three race categories lost significance when tested with county poverty; the third lost significance when tested with sprawl. The reduced model is presented.

coeff. = coefficient

SE = standard error

FPL = federal poverty level

NS = not significant

race/ethnicity variables were dropped. County poverty had a positive association with BMI (Table 3, Model 2, coefficient 8.3, $p<0.001$), and the model explained 47% of the variance. Thus, the association of county racial/ethnic characteristics that initially appeared was actually explained by county poverty, which is a robust predictive variable.

Sprawl

County poverty was next tested with sprawl. Both county poverty and sprawl had significant associations with BMI (Table 3, Model 3). The sprawl index had a significant coefficient (−0.013, $p<0.001$) in the expected direction to indicate that more sprawl is associated with higher BMI. The sprawl index is structured so that more compact counties will have a higher score and more sprawling ones will have a lower score. County poverty remained significant ($p<0.001$) and retained the magnitude of the coefficient (8.9), which indicated that sprawl was measuring a different, additional process than county poverty. The overall model explained 58% of the county-level variance.

Restaurants

The proportion of chain restaurants (Table 3, Model 4) was a significant predictor of BMI, even when controlling for county poverty and sprawl. The coefficient for chain restaurants was large and positive (coefficient 21.337, $p<0.05$), indicating that as the proportion of chain restaurants in a county increased, so did BMI. In this case, the relationship of county poverty was not greatly influenced, and sprawl, poverty, and chain restaurants were all associated with BMI. The overall model was significant at $p<0.001$ and explained 71% of the county-level variance.

Like chain restaurants, the proportion of fast-food restaurants (Table 3, Model 5) was significantly associated with BMI after controlling for county poverty and sprawl. The coefficient for fast-food restaurants was positive (coefficient 8.62, $p<0.01$), indicating that as the proportion of fast-food restaurants in a county increased, so did BMI. In this case, the effect of county poverty was slightly reduced to a coefficient of 5.83, down from 8.94 in the model with only county poverty and sprawl. Sprawl was of a similar magnitude. This finding indicates that some of the associations of county poverty were expressed through fast-food restaurants, but that sprawl, poverty, and fast-food restaurants were all associated with BMI. The overall model was significant at $p<0.001$ and explained 76% of the county-level variance.

Independently owned restaurants (Table 3, Model 6) had a large, negative association to BMI (coefficient −8.254, $p<0.001$), meaning that as the proportion of independent restaurants in a county increased, the BMI decreased. In this model, the presence of independent restaurants absorbed the associations of sprawl, which lost significance. County poverty lost magnitude, dropping from 8.9 in the model without the restaurants to 4.1 when the restaurants were included. The overall relationship of independent restaurants to BMI was different from the other two restaurant categories. County poverty retained a significant relationship, so the inverse relationship with independent restaurants was not acting as a proxy for county poverty, but some of the associations between county poverty and BMI are expressed through independent restaurants. Overall, the model had a Chi-square of $p<0.001$ and explained 75% of the county-level variance.

DISCUSSION

County poverty

Of the causal variables of interest, county poverty was consistently significant with a positive relationship to BMI in all models. This evidence supports the argument that BMI is, in part, associated with of the degree of structural poverty, defined in this study as the proportion of people in a county living at ≤130% of FPL. This finding is an empirical example of theoretical assertions that the societal relationships that perpetuate poverty and inequality are strong causal forces.[12–14,29] It is also noteworthy that individual annual income of <$15,000 was not a significant level-1 predictor of BMI in the models, and especially not in the restaurant models. This demonstrates how poverty is a structural problem and has implications beyond that of individual characteristics. However, very few published studies exist to which comparisons about the role of poverty on BMI can be made. This finding reiterates the importance of including county poverty in other studies and reviews about BMI and the food environment,[1,19] which, as a body of research, include measures of structural poverty only rarely.

Sprawl

Sprawl has an association to BMI in addition to what county poverty contributes. The magnitude of the county poverty coefficient changed little with the addition of sprawl, and more variance in the overall model was explained when sprawl was included, so these variables appear to be measuring different processes that are complementary in their associations to BMI. As a methodological note, the sprawl measure appears to function similarly in this current study as it did when it was used in other studies.[26]

Restaurants

Drawing comparisons from the findings of this analysis to the published literature is limited because "restaurants" are often grouped by only fast-food and full-service (or non-fast-food) varieties. In this study, there is added specificity from separating independently owned and operated full-service restaurants from chain full-service restaurants, for which very different relationships to BMI were demonstrated. Categorizing restaurants in three groups clarifies different relationships for each restaurant type and suggests that measurement differences may account for some inconsistencies in the published literature that combined all full-service restaurants. Thus, the findings in this current study inform the measurement of restaurants as they are used in environmental-level studies about the role of various types of restaurants and the relationships to adult BMI.

Fast food. The association between fast food and BMI was consistent with other research. Finding this relationship after controlling for poverty and sprawl was a unique contribution. Mehta and Chang[7] used national BRFSS data grouped by county and controlled for population size and median household income, which are components of how measures of sprawl and poverty are derived, but essentially different measures. They used the number of fast-food restaurants per 100,000 people as the store measure (restaurant density),[7] rather than a proportion of the total built food environment. Their model explained 18% of the level-2 variance, compared with 24.3% in this analysis. The overall results of both research approaches indicated the same relationship, but including sprawl and poverty in the analysis explained additional county-level variance.

While the results from this study are consistent with those of Mehta and Chang[7] and Maddock,[8] it should be noted that studies conducted in regions smaller than counties report mixed results.[5,6,11] The link between an individual's consumption of fast food and BMI is much more established than the link between an individual's exposure or proximity to fast food and BMI.

Chain and independent restaurants. Published literature groups chain restaurants and independent restaurants together. For example, Mehta and Chang conducted a study similar to this one, but they grouped restaurants as "full service," which included chain and independently owned restaurants. In that study, restaurant density was associated with a lower risk of obesity.[7] Inagami et al. also grouped restaurants in a multilevel study, but found that a higher concentration of restaurants was associated with higher BMI.[30] This current research examined the separate effects of chain and independent restaurants. Chain restaurants had a very strong, positive relationship to BMI after controlling for sprawl and poverty. Understanding the association between chain restaurants and BMI may become more important as menu-labeling laws, which target chain restaurants,[31] are proposed and implemented.

Contrary to fast-food and chain restaurants, independent restaurants had a negative relationship to BMI that absorbed some effects of sprawl and poverty, and were more related to land use and structural economic conditions. Mehta and Chang[7] used a ratio of full-service to fast-service restaurants, and a county with a higher density of full-service restaurants was associated with lower BMI. This finding was similar to the finding that counties with more independent restaurants had lower BMI, but it would be contrary to the finding for chain restaurants, which are also full service. In California, independent restaurants comprise approximately 42% of the food environment, and chain restaurants 4% (Table 1). Thus, research that has not differentiated the two types of full-service restaurant could have been measuring the proportionally larger presence of independent restaurants, which could obscure the opposite effects from chain restaurants.

Limitations

The outcome variable for this research project was BMI, and although significant relationships were demonstrated, there is a long causal pathway from the presence of restaurants, sprawl, and poverty to BMI. This study contributes to a structural explanation of BMI by including a series of generally understudied causal variables.

The predictor variables for restaurants were constructed as a proportion of the total food environment. This method was chosen so that the total food environment would be represented in the measure, reflecting the environmental structure. Other previous work used a retail food environment index, though not specifically linked to a health outcome,[32] but this work made a composition index familiar and intellectually accessible to health professionals. A limitation to the construction of measures in this study, however, is that the three restaurant variables are inherently correlated. The relationships between county poverty, sprawl, and restaurant type are delineated, but not the compounded relationship of all restaurant types to BMI.

This research included only 33 of California's 58 counties. The counties that were included are the largest, most urbanized in the state, while the excluded counties were more rural with smaller populations. The population of the included counties represented 97%

of the state's population, but the findings should be applied only to the counties that were actually included, and the findings do not generally inform large rural areas. The overall results of this work may provide useful ideas for the excluded counties and, in particular, for the larger cities in those counties.

CONCLUSIONS

This study demonstrated environmental associations of poverty and sprawl on BMI for people living in larger, generally urban California counties. County poverty had a robust, large, positive effect on BMI. Sprawl also contributed to the structural explanation. Both of these factors were somewhat reduced when restaurants were added to an explanation. Of particular importance is that independently owned and operated restaurants were associated with reduced BMI, while chain restaurants and fast-food restaurants had strong, positive associations with increased BMI. These variables explained 71% to 76% of the county-level variance. Thus, restaurants, sprawl, and county poverty contribute to a comprehensive structural explanation of BMI, and these factors should be included in future research on this topic.

This study was conducted as dissertation research at the University of California, Davis, Department of Sociology. The Network for a Healthy California, where the author was concurrently employed, provided the use of Dun & Bradstreet data. The results are the findings of the author and do not necessarily reflect opinions of the California Department of Public Health.

REFERENCES

1. Larson NI, Storey MT, Nelson MC. Neighborhood environments: disparities in access to healthy foods in the US. Am J Prev Med 2009;36:74-81.
2. Centers for Disease Control and Prevention (US). Behavioral Risk Factor Surveillance System [cited 2005 Dec 15]. Available from: URL: http://www.cdc.gov/brfss/pubs/index.htm
3. McCann B, Ewing R. Measuring the health effects of sprawl: a national analysis of physical activity, obesity and chronic disease. Washington: Smart Growth America, Surface Transportation Policy Project; 2003.
4. Bowman SA, Vinyard BT. Fast food consumption of US adults: impact on energy and nutrient intakes and overweight status. J Am Coll Nutr 2004;23:163-8.
5. Rundle A, Neckerman KM, Freeman L, Lovasi GS, Purciel M, Quinn J, et al. Neighborhood food environment and walkability predict obesity in New York City. Environ Health Perspect 2009;117:442-7.
6. Wang MC, Kim S, Gonzalez AA, MacLeod KE, Winkleby MA. Socioeconomic and food-related physical characteristics of the neighbourhood environment are associated with body mass index. J Epidemiol Community Health 2007;61:491-8.
7. Mehta NK, Chang VW. Weight status and restaurant availability: a multilevel analysis. Am J Prev Med 2008;34:127-33.
8. Maddock J. The relationship between obesity and the prevalence of fast food restaurants: state-level analysis. Am J Health Promot 2004; 19:137-43.
9. Sturm R, Datar A. Body mass index in elementary school children, metropolitan area food prices and food outlet density. Public Health 2005;119:1059-68.
10. Powell LM, Auld MC, Chaloupka FJ, O'Malley PM, Johnston LD. Access to fast food and food prices: relationship with fruit and vegetable consumption and overweight among adolescents. Adv Health Econ Health Serv Res 2007;17:23-48.
11. Jeffery RW, Baxter J, McGuire M, Linde J. Are fast food restaurants an environmental risk factor for obesity? Int J Behav Nutr Phys Act 2006;3:2.
12. Kreiger N. Why epidemiologists cannot afford to ignore poverty. Epidemiology 2007;18:658-63.
13. Wilkinson RG, Pickett KE. Income inequality and population health: a review and explanation of the evidence. Soc Sci Med 2006; 62:1768-84.
14. Mayer SE, Sarin A. Some mechanisms linking economic inequality and infant mortality. Soc Sci Med 2005;60:439-55.
15. Frank LD, Engelke PO, Schmid TL. Health and community design: the impact of the built environment on physical activity. Washington: Island Press; 2003.
16. Weinberg Z, Epstein MS. Factors affecting supermarket development in inner cities. In: No place to shop: challenges and opportunities facing the development of supermarkets in urban America. Washington: Public Voice for Food and Health Policy; 1996. p. 13-36.
17. Frumkin H. Urban sprawl and public health. Public Health Rep 2002;117:201-17.
18. Frumkin H, Frank L, Jackson R. Urban sprawl and public health: designing, planning and building for healthy communities. Washington: Island Press; 2004.
19. Story M, Kaphingst KM, Robinson-O'Brien R, Glanz K. Creating healthy food and eating environments: policy and environmental approaches. Annu Rev Public Health 2008;29:253-72.
20. California Department of Public Health, Chronic Disease Surveillance and Research Branch, Survey Research Group Section. California Behavioral Risk Factor Surveillance System [cited 2008 Nov 14]. Available from: URL: http://www.surveyresearchgroup.com/sub.php?page=data
21. Chang VW. Racial residential segregation and weight status among US adults. Soc Sci Med 2006;63:1289-303.
22. Chang VW, Christakis NA. Income inequality and weight status in US metropolitan areas. Soc Sci Med 2005;61:83-96.
23. California Department of Health Care Services, California Department of Public Health. California food guide [cited 2010 Jul 30]. Available from: URL: http://www.cafoodguide.ca.gov
24. Dun & Bradstreet, Inc. California food retailers, downloadable data. Short Hills (NJ): Dun & Bradstreet, Inc.; 2004.
25. Ewing R, Pendall R, Chen D. Measuring sprawl and its impact. Washington: Smart Growth America; 2003.
26. Ewing R, Schmid T, Killingsworth R, Zlot A, Raudenbush S. Relationship between urban sprawl and physical activity, obesity, and morbidity. Am J Health Promot 2003;18:47-57.
27. Scientific Software International, Inc. HLM: Version 6.06. Lincolnwood (IL): SSI, Inc.; 2004–2009.
28. Department of Health and Human Services (US), National Institutes of Health, National Heart Lung and Blood Institute. The practical guide: identification, evaluation, and treatment of overweight and obesity in adults [cited 2009 Mar 4]. Available from: URL: http://www.nhlbi.nih.gov/guidelines/obesity/practgde.htm
29. Wilkinson RG, Pickett KE. Income inequality and social dysfunction. Annu Rev Sociol 2009;35:493-511.
30. Inagami S, Cohen DA, Brown AF, Asch SM. Body mass index, neighborhood fast food and restaurant concentration, and car ownership. J Urban Health 2009;86:683-95.
31. Center for Science in the Public Interest. Menu labeling [cited 2010 Nov 3]. Available from: URL: http://www.cspinet.org/menulabeling
32. California Center for Public Health Advocacy. Detailed methodology, searching for healthy food: the food landscape in California cities and counties [cited 2010 Oct 21]. Available from: URL: http://www.publichealthadvocacy.org/RFEI/expanded%20methods.pdf