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RESEARCH ARTICLE

Obesity Prevention: The Impact of Local Health Departments

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Objective. To examine the association between bodyweight status and provision of population-based prevention services.

Data Sources. The National Association of City and County Health Officials 2005 Profile survey data, linked with two cross-sections of the Behavioral Risk Factor Surveillance System (BRFSS) survey in 2004 and 2005.

Study Design. Multilevel logistic regressions were used to examine the association between provision of obesity-prevention services and the change in risk of being obese or morbidly obese among BRFSS respondents. The estimation sample was stratified by sex. Low-income samples were also examined. Falsification tests were used to determine whether there is counterevidence.

Principal Findings. Provision of population-based obesity-prevention services within the jurisdiction of local health departments and specifically those provided by the local health departments are associated with reduced risks of obesity and morbid obesity from 2004 to 2005. The magnitude of the association appears to be stronger among low-income populations and among women. Results of the falsification tests provide additional support of the main findings.

Conclusions. Population-based obesity-prevention services may be useful in containing the obesity epidemic.

Key Words. Behavioral risk factor surveillance system, multilevel logit, local health departments, obesity prevention

Obesity is associated with increased risks of chronic diseases, including type 2 diabetes, hypertension, stroke, heart disease, and certain cancers (National Institutes of Health [NIH] 1998), as well as high and rising medical spending (Thorpe et al. 2004). The prevalence of obesity in the United States has reached an epidemic level even with some recent signs of temporary leveling off (Flegal et al. 2010; Ogden et al. 2010). Enhancing the role of the public health system in containing the obesity epidemic and associated health care burden is of major concern to public health researchers, practitioners, and policy makers (Huberty et al. 2010).

The existing research has examined strategies and interventions to contain the obesity epidemic, which include changes in national or state tax rates on certain food and beverage items, regulations on food marketing, and food-labeling legislations (Pomeranz et al. 2009; Powell and Chaloupka 2009; Powell, Chriqui, and Chaloupka 2009; Powell, Szczypka, and Chaloupka 2010; Sturm et al. 2010). The role of local health departments in obesity prevention has only recently received attention from a handful of researchers; see, for example, Slater, Powell, and Chaloupka (2007), Zhang et al. (2010), Schwarte et al. (2010), and Pomeranz (2011). These researchers suggest that local health departments could have a critical role in containing the obesity epidemic. This study is the first to examine the association between obesity-prevention services provided in a county jurisdiction and the change in body-weight status among the Behavioral Risk Factor Surveillance System (BRFSS) survey respondents. In addition, we investigate whether such an association is stronger among low-income populations, who might have the greatest need for such services (Metz, Cioffi, and Lichtveld 2003). The results show that the provision of obesity-prevention services is associated with a reduction in the risks of obesity and morbid obesity from 2004 to 2005 and the association among low-income populations is stronger.

ROLE OF LOCAL HEALTH DEPARTMENTS IN REDUCING OBESITY

Local and state health departments are a crucial component of the U.S. public health system, which can be viewed as a federation that comprises state, county, city, and tribal health departments, federal agencies that sponsor or engage in public health services, as well as health care providers, and non-profit and community organizations that promote population health (Altman and Morgan 1983; Lister 2005). Assessing the impact of public health services

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provided by local health departments is useful to enhance capacity of the U.S. public health system to address public health problems and improve the nation's health, and reduce health disparities (Mays, Halverson, and Scutchfield 2003; Mays et al. 2004; Grembowski et al. 2010). Erwin summarized several critical research areas in assessing the role and effectiveness of local health departments, which include the following: the interventions that local health departments have implemented, the effectiveness of such interventions, and potential improvements over the current infrastructure (Erwin 2008).

The role of local health departments has traditionally focused on communicable disease control, and more recently on emergency preparedness and response. However, with noncommunicable diseases accounting for 80 percent of deaths in the United States, local health departments have taken on the new responsibility of preventing and controlling chronic diseases (Frieden 2004). The study by Slater, Powell, and Chaloupka (2007) was one of the few studies that assessed the role of local health departments in obesity prevention. The authors reported that <50 percent of health departments in their survey provided, supported, or advocated obesity-prevention programs, although the majority of informants indicated that these programs were considered high priority. Zhang et al. (2010) explored the association between the local health department characteristics and whether they conducted obesity prevention and diabetes screening programs. They found that the presence of obesity-prevention service was significantly associated with the local health department structural capacity and general performance. Mays and Smith (2011) examined the association between cause-specific mortality rates and local public health spending and found that a 10 percent increase in local public health spending reduced deaths from heart disease, diabetes, and cancer by 3.22, 1.44, and 1.13 percent, respectively.

Local health departments can serve a unique role in containing the obesity epidemic. First, as the public health's foot soldiers, staff at a local health department have knowledge of the community they serve and a close relationship with other local agencies and organizations that are key players in obesity prevention. For instance, the Special Supplemental Nutrition Program for Women, Infants, and Children (generally known as the WIC program) and the Supplemental Nutritional Assistance Program (formerly the Food Stamp Program) are implemented by local agencies with federal and state assistance. Both programs could present opportunities for preventive interventions, including but not limited to nutrition education. Second, the diversity of local health departments leads to innovations that might be assessed and disseminated. For instance, California is the first state to enact a statewide menu-labeling

law, and it was preceded by local menu-labeling ordinances passed in San Francisco and Santa Clara (Pomeranz et al. 2009). Although the legislative approaches are different from prevention services, the engagement of local health departments is indispensable given their role in surveillance, health education, and public health advocacy (Frieden 2004).

Schwartz et al. (2010) surveyed local health departments in California and found that local health departments participated in a variety of advocacy and policy change activities for improving nutrition and physical activity environments, including programs to promote healthier eating and/or physical activity in school or after school environments and in worksites (including the health department), and in the involvement in the development, implementation, and/or monitoring of local school wellness policies. Slater, Powell, and Chaloupka (2007) found that health departments have implemented programs, including individual and group nutrition counseling, group or peer weight loss programs, parent education programs to reduce obesity, walking or bike clubs, and so on. Although the programs Slater, Powell, and Chaloupka (2007) examined have focused on obesity prevention among youth, their effects might spill over to adults as parents, caregivers, and staff members were involved in such programs. A field example of obesity-prevention services provided at local health departments is the obesity prevention and control in Pierce County, Washington, as evidenced in a recent report (Frandsen et al. 2009), which proposed built environment, availability of healthy food, and providing support for a healthy eating and active living environment.

Zhang et al. (2010) indicated that the effectiveness and cost-effectiveness of both obesity-prevention services and diabetes screening at local health departments remain unknown. Challenges exist for assessing the effectiveness of obesity-prevention services. First, to meet local needs, obesity-prevention services being offered might differ from one local health department to another. We have to either evaluate an individual prevention service, which is often difficult due to the nonexperimental nature of the services, or lump the different services together into a catch-all category, which averages out the effectiveness across different kinds of obesity-prevention services. Second, few data exist on the obesity-prevention services except the Profile surveys conducted by the National Association of County and City Health Officials (NACCHO). No cost data are available on a large scale for obesity-prevention services conducted by local health departments; thus, a cost-effectiveness evaluation is not currently feasible.

In this article, we were unable to conduct a longitudinal study as data on the obesity-prevention services only exist in the NACCHO Profile 2005

wave. Instead, we examine the difference in the change in the risks of being obese (or morbidly obese) between counties with and without obesity-prevention services. Our approach reduces the likelihood that the estimated association is due to reverse causality. We used falsification tests to examine whether the observed association is due to unobserved characteristics or a general preference of healthy lifestyle among residents in the jurisdiction.

METHODS

Data

We merged data from the NACCHO Profile 2005 survey with two waves (2004–2005) of BRFSS survey (NACCHO 2006; Centers for Disease Control and Prevention [CDC] 2006). The NACCHO Profile is a census of all local health departments (including both county and city health departments) with comprehensive information regarding jurisdiction, governance, financing, characteristics of top executives, workforce, activities and services, planning and performance improvement, partnerships, policy-making activities, and information technology use among the local health departments. The NACCHO 2005 Profile had a response rate of 80 percent, resulting in 2,300 valid responses. The Profile data had been used in previous studies to examine spending by local health departments (Mays and Smith 2009; Santerre 2009).

BRFSS is a state-based health survey that tracks information related to individual health conditions, risky behaviors, preventive health practices, and health care access primarily related to chronic disease and injury among the noninstitutionalized U.S. population of adults aged ≥ 18 years (Fan et al. 2010). BRFSS responses are collected by state health departments, using computer-assisted telephone interviews, with coordination from the CDC.

Although BRFSS provides Federal Information Processing Standards (FIPS) code of the county where the respondent resides, the NACCHO 2005 Profile only has zip codes of the physical location of the local health departments. Thus, we assigned each county health department an identifier by using the zip code-FIPS correspondence, as well as case-by-case individual matching. We also constructed a correspondence table of city/county (combined) health departments and multi-county health departments to FIPS codes, which were used to merge BRFSS data with the NACCHO profile survey data. We, however, could not use the responses from city health departments because county is the finest geographic unit available in the

BRFSS data. Because BRFSS is not intended to include every county, merging with BRFSS reduces the number of counties to 1,099. The final study sample includes 415,348 BRFSS responses from 1,099 counties during 2004–2005.

Dependent Variables

We constructed two dependent variables to measure obesity and morbid obesity on the basis of body mass index (BMI: body weight in kilograms divided by height in meters squared). A person was considered obese if he or she had a BMI ≥ 30 , and morbidly obese if his or her BMI was ≥ 40 (NIH, 1998). Body weight and height were self-reported by BRFSS respondents.

Explanatory Variables of Interest

A set of binary indicators are available in the NACCHO Profile Survey to measure availability and identify the provider of obesity-prevention services. The responses were reported by officials at local health departments, and thus, measurement errors might exist when they report whether prevention services were available through *other* agencies or *contractors*. Hence, we choose not to use the binary indicators of obesity-prevention service availability through other agencies or contractors. The two binary variables indicating “obesity-prevention service available through the local health department” (q67a) and “obesity-prevention service *not* available in the jurisdiction” (q67f) are used in the regressions. The variable q67f is one if no obesity-prevention service is available from any institution within the jurisdiction, including local health department, contractor, state health department, and others, and zero otherwise. Note that only less than 5 percent of the local health departments in the study sample do not have any obesity-prevention service in their jurisdiction, but there is a larger variation in the availability of obesity-prevention services from the local health department.

Independent Variables

Individual-level variables included in the analysis were indicators of age, race (non-Hispanic white, non-Hispanic black, Asian, native Hawaiian or other Pacific Islander, American Indian or Alaskan Native, other non-Hispanic, non-Hispanic multiracial, Hispanic, don't know), marital status (married, divorced, widowed, separated, never married, a member of an

unmarried couple, refused), education (never attended school or only kindergarten, elementary, some high school, high school, some college, college and above, refused), income (less than \$10,000, \$10,000–15,000, \$15,000–\$20,000, \$20,000–\$25,000, \$25,000–\$35,000, \$35,000–\$50,000, \$50,000–\$75,000, more than \$75,000, don't know/not sure, refused), employment status (employed, self-employed, out of work for more than 1 year, out of work for less than 1 year, a homemaker, a student, retired, unable to work, refused), household size and its squared term, number of children and its squared term, dummy variables indicating month of interview, and sex when pooling both men and women together (Table 2). In the BRFSS data file released on the CDC website, the age variable was recoded into binary variables indicating 5-year intervals, which were used to construct age splines for functional flexibility. To control for county-level factors that may be related to obesity, we extracted data from the Area Resource File to construct two county-level variables, a variable indicating the extent of urbanization of the county, and the median household income in the county, both of which were used in our analysis.

STATISTICAL ANALYSIS

Analytic Method

Multilevel logistic regression was used to estimate the association between obesity-prevention services provision and the risks of being obese or morbidly obese among BRFSS respondents (Guo and Zhao 2000; Li et al. 2006). The model has three levels, that is, individual, county, and state. We assume state fixed effects to control for unobserved heterogeneity in state policy, climate, and geography that might affect bodyweight. We also assume an independent correlation structure among measurements taken on persons within a county. All regressions were weighted using the final weights provided in the BRFSS data file. Generalized linear mixed model was used in all regressions.

Let y_{ijk} indicate the bodyweight status of individual k in county j of state i at time period t . It is one if the person is obese (morbidly obese) and zero otherwise. We assume the probability of $y_{ijk} = 1$ as $p_{ijk} = \Pr(y_{ijk} = 1)$ with a Bernoulli distributional assumption and model p_{ijk} using a logit link function. Denote the individual characteristics as x_{ijk} , and β is a conformable parameter vector. T_{ijk} is a binary indicator that is one if the person was interviewed in 2005, and zero if interviewed in 2004. d_{ij} is a binary indicator on provision of

obesity-prevention service in the jurisdiction (q67a or q67f). We use both q67a and q67f to evaluate the association between bodyweight status among BRFSS participants and obesity-prevention services provided in a county specifically by the county health departments and in general. The s_s are the state fixed effects and c_{js} are the county random effects. We include in the regressions an interaction term of the time dummy T_{ijk} and the service provision dummy variable d_{ij} . The multilevel model is as follows.

$$\log\left[\frac{p_{ijk}}{1 - p_{ijk}}\right] = x_{ijk}\beta + \delta_1 T_{ijk} + \delta_2 d_{ij} + \delta_3 T_{ijk} \cdot d_{ij} + s_i + c_{ij}$$

The variable T_{ijk} captures the difference between the two time periods (2005 vs. 2004) that is due to time trend or other unobserved variables. The survey asked respondents whether the organizations in their jurisdiction had conducted the activity or service during the past year. Respondents returned the responses during a 4-month period from June to October 2005. Therefore, the year 2004 is used as the baseline year, whereas the year 2005 is considered the time period that the effects of obesity-prevention service may be realized. The variable d_{ij} captures the difference in bodyweight associated with the service provision variable. However, the effect could be related to unobserved difference between county health departments that offer obesity prevention and those do not, or the difference in economic and other conditions between those counties.

We use the interaction term of the time dummy T_{ijk} and the service provision dummy variable d_{ij} to evaluate the change in bodyweight associated with the obesity-prevention services reported in the NACCHO 2005 Profile survey. The interaction term is interpreted as the changes in bodyweight status associated with the service provision variable d_{ij} and is the key regressor of interest.

Two sets of models were estimated. The first set of 12 regressions addresses two questions—is there an association between obesity-prevention services provided through local health departments and reduced likelihood of being obese or morbidly obese? Is the association stronger for the low-income population? Two dependent variables, obesity and morbid obesity, were regressed on the binary indicator of whether obesity-prevention services are available through local health departments (q67a) and other control variables by using the pooled sample and two subsamples that were stratified by sex, resulting in six regressions. Then, the same models were also fitted to low-income samples, which included only those with annual income <\$35,000.¹ The second set of models regress the two dependent variables on a binary

indicator of no obesity-prevention services provided within the county. Regression samples, again, include both sexes and stratified for men and women, and for both the combined sample of all-income levels and the low-income sample.

All statistical analyses were conducted using SAS GLIMMIX Procedure (SAS Institute 2005).

Falsification Test

A falsification test, also termed as anti-test or placebo test, provides counter evidence by examining a model or identification strategy in a context that differs from the main regression setting (Jones 2009; Howard et al. 2010). We conduct two falsification tests. First, we matched the BRFSS 2001–2002 data with the NACCHO Profile 2005 Survey. The regression models estimate the association between obesity-prevention services reported in the Profile 2005 survey and the change in bodyweight status from 2001 to 2002. Second, we changed the dependent variable to a binary variable of self-reported flu vaccination within last 12 months; thus, the regressions estimate the association between obesity-prevention services and the change in *flu vaccination* during 2004–2005.

RESULTS

Descriptive Statistics

Table 1 provides the summary statistics of individual characteristics for respondents in both the study sample and in the full BRFSS sample. The two samples have only some trivial differences and the study sample comprises roughly three-fourths of the full sample. Hence, the study represents the full BRFSS sample quite well.

Regression Results

Table 2 presents the multilevel logistic regression coefficient estimates of the interaction term of the 2005 year effect (baseline: year 2004) and a binary variable indicating availability of obesity-prevention services through local health departments. We reported coefficient estimates but not odds ratio because of the difficulties in interpreting odds ratio given our focus on interaction terms. We also calculate differences in changes in the *predicted* probability of obesity

Table 1: Comparing the Individual-Level Characteristics between Behavioral Risk Factor Surveillance System (BRFSS) 2004–2005 Study Sample and the Full Sample

Variable	BRFSS 2004–2005 Study Sample		BRFSS 2004–2005 Full Sample			
	Pooled	Men	Women	Pooled	Men	Women
Number of individuals	415,348	166,264	249,084	561,815	225,318	336,497
BMI (kg/m ²)	26.982	27.429	26.526	26.957	27.410	26.499
Obesity (%)	0.236	0.241	0.232	0.234	0.238	0.230
Morbid obesity (%)	0.029	0.021	0.036	0.028	0.021	0.035
Male	0.505			0.503		
Married (reference)	0.588	0.618	0.559	0.583	0.614	0.552
Divorced	0.094	0.078	0.110	0.093	0.077	0.110
Widowed	0.064	0.027	0.101	0.065	0.028	0.102
Separated	0.021	0.016	0.027	0.022	0.016	0.028
Never married	0.189	0.214	0.163	0.194	0.218	0.169
A member of an unmarried couple	0.041	0.045	0.037	0.041	0.045	0.037
Refused (marital status)	0.002	0.002	0.002	0.002	0.002	0.002
Never attended school or only kindergarten (reference)	0.001	0.001	0.002	0.002	0.002	0.002
Grades 1–8 (elementary)	0.037	0.039	0.035	0.036	0.037	0.035
Grades 9–11 (some high school)	0.073	0.073	0.072	0.072	0.072	0.072
Grade 12 or GED (high school graduate)	0.278	0.270	0.287	0.280	0.273	0.288
College 1–3 years (some college or technical school)	0.271	0.255	0.288	0.266	0.252	0.281

continued

Table 1. *Continued*

Variable	BRFSS 2004-2005 Study Sample			BRFSS 2004-2005 Full Sample		
	Pooled	Men	Women	Pooled	Men	Women
College 4 years or more (college graduate)	0.338	0.360	0.316	0.343	0.364	0.321
Refused (education)	0.001	0.001	0.001	0.001	0.002	0.001
Less than \$10,000 (reference)	0.046	0.036	0.057	0.047	0.036	0.057
\$10,000 to less than \$15,000	0.047	0.039	0.055	0.047	0.039	0.055
\$15,000 to less than \$20,000	0.065	0.058	0.071	0.065	0.057	0.072
\$20,000 to less than \$25,000	0.079	0.076	0.082	0.079	0.076	0.081
\$25,000 to less than \$35,000	0.110	0.110	0.110	0.110	0.109	0.110
\$35,000 to less than \$50,000	0.142	0.148	0.136	0.142	0.148	0.135
\$50,000 to less than \$75,000	0.157	0.167	0.147	0.156	0.165	0.146
\$75,000 or more	0.237	0.267	0.206	0.237	0.268	0.206
Don't know/not sure (income)	0.056	0.044	0.068	0.058	0.046	0.070
Refused (income)	0.061	0.055	0.067	0.061	0.055	0.067
Employed for wages (reference)	0.535	0.594	0.474	0.534	0.592	0.476
Self-employed	0.087	0.110	0.064	0.087	0.111	0.063
Out of work for more than 1 year	0.021	0.020	0.022	0.022	0.020	0.023
Out of work for less than 1 year	0.031	0.034	0.028	0.031	0.034	0.028
A homemaker	0.074	0.003	0.146	0.073	0.003	0.144
A student	0.047	0.045	0.049	0.048	0.046	0.050
Retired	0.159	0.153	0.165	0.158	0.152	0.164
Unable to work	0.044	0.038	0.050	0.045	0.039	0.050
Refused (employment status)	0.002	0.002	0.002	0.002	0.002	0.002

continued

Table 1. Continued

Variable	BRFSS 2004-2005 Study Sample		BRFSS 2004-2005 Full Sample			
	Pooled	Men	Women	Pooled	Men	Women
White only, non-Hispanic (reference)	0.681	0.676	0.687	0.678	0.674	0.682
Black only, non-Hispanic	0.101	0.093	0.110	0.105	0.095	0.114
Asian only, non-Hispanic	0.028	0.031	0.025	0.028	0.032	0.025
Native Hawaiian or other Pacific Islander only, Non-Hispanic	0.004	0.004	0.003	0.004	0.004	0.003
American Indian or Alaskan native only, non-Hispanic	0.010	0.011	0.010	0.010	0.010	0.009
Other race only, non-Hispanic	0.007	0.009	0.006	0.008	0.010	0.007
Multiracial, non-Hispanic	0.015	0.015	0.014	0.014	0.015	0.014
Hispanic	0.146	0.154	0.139	0.145	0.151	0.139
Don't know/not sure/refused (race/ethnicity)	0.007	0.008	0.006	0.007	0.009	0.006
Age (year)	0.821	0.788	0.854	45.638	44.404	46.891
Number of children	45.582	44.353	46.839	0.808	0.775	0.841
Household size	3.078	3.121	3.035	3.062	3.106	3.016

Note. For the age variable, missing values resulted in slightly lower number of observations. The mean age is provided for reference but not used in the regressions. A set of imputed 5-year categorical indicators of age is used in the regressions. All estimates are weighted.

Table 2: Multilevel Logistic Regressions: Effect of Obesity-Prevention Service Provided through Local Health Departments (q67a) on Obesity

Dependent Variable	Pooled Sample			Men			Women					
	CE	p-Value	SE	PM	CE	p-Value	SE	PM	CE	p-Value	SE	PM
All-income levels												
DV: Obesity	-0.0108	<.0001	0.0007	-0.0019	0.0162	<.0001	0.0009	0.0028	-0.0268	<.0001	0.0009	-0.0045
DV: Morbid obesity	-0.0194	<.0001	0.0017	-0.0004	0.0133	<.0001	0.0024	0.0002	-0.0229	<.0001	0.0021	-0.0004
Low-income sample (income <\$35,000)												
DV: Obesity	0.0152	<.0001	0.0011	0.0032	0.0500	<.0001	0.0018	0.0093	0.0028	0.0716	0.0015	0.0007
DV: Morbid obesity	-0.0307	<.0001	0.0024	-0.0010	0.0013	0.7298	0.0039	0.0014	-0.0389	<.0001	0.0030	-0.0014

Control variables include the following: at individual-level, household size and its squared term, number of children and its squared term, 5-year inter-val age indicators, gender (when pooled), marital status, education, employment, income, race, interview month; at county/local health department level, health department organization, county urbanization code, county-level median household income variable; and an indicator of year 2005 (base-line: year 2004).

The model used is a multilevel logistic regression with three levels: individual, county, and state. State specific intercepts are assumed to be fixed. CE, coefficient estimate; DV, dependent variable; PM, predicted marginal (calculated as the difference in the changes of the predicted probabilities of [morbid] obesity from 2004 to 2005 between those residing in counties with a positive response to q67a and those residing in counties with a negative response).

from 2004 to 2005 between those residing in counties with a positive response to q67a or q67f (i.e., access to obesity-prevention services) and those resided in counties with a negative response. Results are reported separately for the sample with all-income levels and the low-income sample, and for both the pooled sample and the subsamples stratified by sex.

Results for the all-income sample support an association between the provision of obesity-prevention services through local health departments and the reduced risks of obesity and morbid obesity for the pooled sample. However, the coefficient in the obesity specification for the male sample suggest an increase in the risk of obesity from 2004 to 2005 among those residing in a county with obesity-prevention services provided through local health departments. Results for women show that those residing in counties with obesity-prevention services provided through local health departments have a larger decrease (or a smaller increase) from 2004 to 2005 in the probability of obesity and morbid obesity by 0.45 and 0.04 percent, respectively, compared with those residing in counties without obesity-prevention services provided through local health departments.

In the pooled sample, low-income respondents residing in counties with obesity-prevention services provided through the local health departments have reduced risk of obesity and morbid obesity from 2004 to 2005. Results for low-income men are not statistically significant in the specification for morbid obesity. Low-income women residing in counties with obesity-prevention services provided through local health departments have larger decrease (or smaller increase) from 2004 to 2005 in the probability of morbid obesity by 0.14 percent, compared with those residing in counties without obesity-prevention services provided through local health departments.

Table 3 shows the results of multilevel logistic regressions of obesity and morbid obesity. Each cell contains the coefficient estimate of the interaction term between the year 2005 (baseline: year 2004) effect and the binary indicator of *no obesity-prevention services* (reported by respondents to the NACCHO Profile 2005 survey). Respondents residing in counties without obesity-prevention services have larger increase (or smaller decrease) from 2004 to 2005 in the probability of obesity and morbid obesity by 0.27 and 0.49 percent, respectively, compared with those residing in counties with obesity-prevention services. The increase in probability of obesity and morbid obesity is higher for all low-income respondents, and even higher among low-income women (2.4 and 3.5 percent, respectively) residing in counties without access to obesity-prevention services.

Table 3: Multilevel Regressions: Effect of No Obesity-Prevention Service in Jurisdiction (q67f) on Obesity

Dependent Variable (DV)	Pooled Sample				Men				Women			
	CE	p-Value	SE	PM	CE	p-Value	SE	PM	CE	p-Value	SE	PM
All-income levels												
	N = 415,348				N = 166,264				N = 249,084			
DV: Obesity	0.0149	<0001	0.0017	0.0027	-0.0457	<0001	0.0024	-0.0079	0.0686	<0001	0.0025	0.0118
DV: Morbid obesity	0.2267	<0001	0.0044	0.0049	0.0855	<0001	0.0071	0.0015	0.2690	<0001	0.0055	0.0064
Low-income sample (income <\$35,000)												
	N = 118,972				N = 40,689				N = 78,283			
DV: Obesity	0.1051	<0001	0.0034	0.0232	0.1110	<0001	0.0054	0.0218	0.1133	<0001	0.0046	0.0244
DV: Morbid obesity	0.4986	<0001	0.0074	0.0161	-0.0082	0.4785	0.0115	-0.0082	0.7705	<0001	0.0087	0.0352

Control variables include the following: at individual-level, household size and its squared term, number of children and its squared term, 5-year inter-val age indicators, gender (when pooled), marital status, education, employment, income, race, interview month; at county/local health department level, health department organization, county urbanization code, county-level median household income variable; and an indicator of year 2005 (base-line; year 2004).
 The model used is a multilevel logistic regression with three levels: individual, county, and state. State specific intercepts are assumed to be fixed. CE, coefficient estimate; DV, dependent variable; PM, predicted marginal (calculated as the difference in the changes of the predicted probabilities of [morbid] obesity from 2004 to 2005 between those residing in counties with a positive response to q67a and those residing in counties with a negative response).

Falsification Test Results

Table 4 summarizes the results from the multilevel logistic regressions using the BRFSS 2001–2002 waves merged with the NACCHO Profile 2005 survey. The results are generally not consistent between those for obesity and for morbid obesity. Obesity-prevention services provided through local health departments are associated with an increase in the change in the probability of morbid obesity but a decrease in the change in the probability of obesity. No obesity-prevention services provided within the jurisdiction are associated with a large increase in the probability of obesity and a smaller increase in the probability of morbid obesity among all-income levels but a smaller increase in both obesity and morbid obesity among low-income populations.

Table 5 summarizes the results from the regressions of a binary variable indicating flu vaccination within last 12 months using the BRFSS 2004–2005 waves merged with the NACCHO Profile 2005 survey. The coefficients of the interaction term were statistically significant but do not offer a consistent interpretation. Obesity-prevention service provided by local health departments is associated with a larger decrease (or smaller increase) in the likelihood of flu vaccination from 2004 to 2005 in nearly all regression samples with the exception of low-income men. However, no obesity-prevention services provided within the jurisdiction are also associated with a larger decrease (or a smaller increase) in the likelihood of flu vaccination from 2004 to 2005.

DISCUSSION

Causal Interpretations

Because the prevention service variables used in this article are not true treatment indicators, we need to be careful in interpreting our results. We, however, can examine several alternative explanations of the association to argue for a causal effect. First, one might suggest that the association is due to responses of local health departments to obesity prevalence in the county. This is not relevant to this study as we are focusing on the interaction term, which is the change in the risk of obesity and morbid obesity from 2004 to 2005. A higher obesity rate could indeed prompt local health departments to provide obesity-prevention services, but this would lead to a downward bias in our estimates. Second, other contributing factors might lead to both higher implementation rate of obesity-prevention services among local health departments and lower level of obesity among BRFSS

Table 4: Falsification Test Results Using Behavioral Risk Factor Surveillance System 2001–2002: Obesity-Prevention Services (2005) and Obesity (Year 2001–2002)

Dependent Variable	Pooled Sample				Men				Women			
	CE	p-Value	SE	PM	CE	p-Value	SE	PM	CE	p-Value	SE	PM
Panel A. q67a: Obesity-prevention service provided through local health departments												
All-income levels												
DV: Obesity	-0.0651	<0001	0.0007	-0.0105	-0.0407	<0001	0.0010	-0.0063	-0.0830	<0001	0.0011	-0.0134
DV: Morbid obesity	0.0488	<0001	0.0019	0.0008	0.0653	<0001	0.0031	0.0007	0.0546	<0001	0.0023	0.0012
Low-income sample (income <\$35,000)												
DV: Obesity	-0.0780	<0001	0.0013	-0.0160	-0.1092	<0001	0.0020	-0.0190	-0.0661	<0001	0.0017	-0.0136
DV: Morbid obesity	0.1386	<0001	0.0026	0.0042	0.0091	0.0413	0.0045	0.0092	-0.0260	<0001	0.0038	-0.0001
Panel B. q67b: No obesity-prevention service in jurisdiction (q67f)												
All-income levels												
DV: Obesity	0.0853	<0001	0.0020	0.0135	0.0858	<0001	0.0028	0.0125	0.0567	<0001	0.0030	0.0097
DV: Morbid obesity	-0.1154	<0001	0.0054	-0.0018	-0.2496	<0001	0.0073	-0.0029	-0.0995	<0001	0.0079	-0.0020
Low-income sample (income <\$35,000)												
DV: Obesity	-0.1747	<0001	0.0041	-0.0359	-0.1458	<0001	0.0066	-0.0245	-0.2939	<0001	0.0054	-0.0627
DV: Morbid obesity	-0.2657	<0001	0.0082	-0.0083	-0.0054	0.6847	0.0133	-0.0054	-0.1507	<0001	0.0156	-0.0003

Control variables include the following: at individual-level, household size and its squared term, number of children and its squared term, 5-year interval age indicators, gender (when pooled), marital status, education, employment, income, race, interview month; at county/local health department level, health department/organization, county urbanization code, county-level median household income variable; and an indicator of year 2005 (baseline: year 2004). The model used is a multilevel logistic regression with three levels: individual, county, and state. State-specific intercepts are assumed to be fixed. CE, coefficient estimate; DV, dependent variable; PM, predicted marginal (calculated as the difference in the changes of the predicted probabilities of [morbid] obesity from 2004 to 2005 between those residing in counties with a positive response to q67a and those residing in counties with a negative response).

Table 5: Falsification Test Results Using Behavioral Risk Factor Surveillance System 2004–2005: Obesity-Prevention Services by LHD and Flu Vaccination (Dependent Variable: Flu Vaccination)

Regressor of Interest	Pooled Sample				Men				Women			
	CE	p-Value	SE	PM	CE	p-Value	SE	PM	CE	p-Value	SE	PM
All-income levels												
		N = 414,359				N = 165,773				N = 248,586		
q67a	-0.0209	<0001	0.0007	-0.0041	-0.0171	<0001	0.0010	-0.0029	-0.0171	<0001	0.0009	-0.0034
q67f	-0.0377	<0001	0.0017	-0.0072	-0.0809	<0001	0.0025	-0.0134	-0.0045	0.0688	0.0025	-0.0011
Low-income sample (income <\$35,000)												
		N = 118,720				N = 40,567				N = 78,153		
q67a	-0.0072	<0001	0.0013	-0.0013	0.1282	<0001	0.0020	0.0182	-0.1230	<0001	0.0018	-0.0224
q67f	-0.1985	<0001	0.0036	-0.0389	-0.4022	<0001	0.0059	-0.0648	-0.0637	<0001	0.0052	-0.0130

Control variables include the following: at individual-level, household size and its squared term, number of children and its squared term, 5-year inter-val age indicators, gender (when pooled), marital status, education, employment, income, race, interview month; at county/local health department level, health department organization, county urbanization code, county-level median household income variable; and an indicator of year 2005 (base-line; year 2004).

The model used is a multilevel logistic regression with three levels: individual, county, and state. State specific intercepts are assumed to be fixed. CE, coefficient estimate; DV, dependent variable; PM, predicted marginal (calculated as the difference in the changes of the predicted probabilities of [morbid] obesity from 2004 to 2005 between those residing in counties with a positive response to q67a and those residing in counties with a negative response).

respondents. However, aside from the direct causal pathways between obesity-prevention service and prevalence of obesity and morbid obesity, determinants underlying obesity and factors leading to provision of obesity-prevention services rarely overlap. For example, state budget shortfall might affect the provision of preventive services but has no *direct* impact on obesity. We do note that other unmeasured confounders might exist and affect the observed association between obesity and the provision of obesity-prevention services. Lastly, measurement error in the dependent variable might be correlated with explanatory variables, but it is unlikely in this study because the variables came from two different sources—residents report their bodyweight while officials at the local health departments report on the provision of obesity-prevention services.

Another question may be raised on a causal interpretation of our results is the time lag after which the effect of obesity-prevention programs is realized. Results from the computational biology suggest that the effect of daily energy imbalance can be realized into body fat in less than a year (Christiansen, Garby, and Sørensen 2005). In addition, obesity-prevention programs often have observable short-term effects, but the impact may not be sustainable and could diminish over time if the program is discontinued (Tuah et al. 2011). It is also worth noting that the timeline of the responses being collected suggests there is sufficient time for the effects of the obesity-prevention programs to be realized. We choose to use the approach outlined earlier but not a model with lagged effects.

Results of the Falsification Tests

The implications from the falsification tests warrant further discussion. We would expect that no association between the dependent variable and the regressor of interest be detected in the falsification specifications. However, the results are mixed on the association between the obesity-prevention services provided by the local health department and an increase in the risk of obesity from 2001 to 2002. Obesity prevention provided through the local health departments is associated with reduced risk of morbid obesity but increased risk of obesity. Lack of obesity-prevention services (from any agency) in the county is associated with increases in obesity and decreases in morbid obesity among all-income levels but is associated with decreases in both obesity and morbid obesity among low-income population. A possible explanation is that a local health department was prompted by an increase in the rates of obesity and morbid obesity during 2001–2002 in its jurisdiction to

seek resources for obesity-prevention programs, which were implemented later on.

The result on flu vaccination can be viewed as a test of whether a general preference over health could lead to the observed association in the main results. The results, in the case of pooled low-income sample, suggest that offering obesity-prevention services through local health departments is associated with lower likelihood of flu vaccination among low-income population. Therefore, our main results are unlikely due to a general preference of healthy lifestyle among BRFSS respondents.

Sex Difference

This article revealed sex differences in the association between the risk of obesity or morbid obesity and the provision of obesity-prevention service with most of the effect of obesity-prevention services stronger among women. The difference coincides with the fact that women comprise a substantial proportion of the low-income population and that they are more likely to be obese (Starrels, Bould, and Nicholas 1994; Wang and Beydoun 2007). Participants of the food assistance programs are more likely to be women (Yen et al. 2008). Integrating obesity-prevention services into food assistance programs might help low-income women who are more susceptible to obesity and morbid obesity.

Low-Income Population

Comparing results for the low-income sample and those for the sample with all-income levels reflects a stronger association between the reduced risks of obesity or morbid obesity and provision of obesity-prevention services among low-income respondents. For instance, the magnitude of the estimated associations among low-income samples is larger than its corresponding estimates for the sample with all-income levels. This confirms that the local health departments generally focus their efforts among low-income population. We were unable to perform a statistical test to confirm whether the differences are statistically significant because of difficulties in doing so for multilevel models.

Limitations

The study has at least three limitations. First, we used self-reported bodyweight and height because no clinically measured anthropometric

information is available. Studies have used the National Health and Nutrition Examination Survey (NHANES) to construct estimated BMI that is used in regressions instead of self-reported BMI. We, however, choose not to do so because empirical results indicate differences between using the original measures and the estimated BMI are minimal. NHANES and BRFSS have different sampling designs and survey procedures; thus, plugging parameters estimated by using NHANES into this study might introduce additional statistical noises (see, e.g., Meltzer and Chen 2011). Second, the regressors of interest are subject to reporting error because reporting officials may have different interpretations of obesity-prevention services. Lastly, although this particular study focused on impact of obesity-prevention services, we acknowledge that obesity-prevention policies on a broad scale could have critical impacts as well (Pomeranz 2011).

CONCLUSIONS AND FUTURE RESEARCH

This study provides evidence that, after controlling for other relevant factors, residents in counties where local health departments provide population-based obesity-prevention services have smaller increases in the risk of obesity or morbid obesity compared with residents living in jurisdictions without provision of such services through local health departments. The association between provision of obesity-prevention service by the local health departments and reduced risks of being obese or morbidly obese is stronger for women, and the result is consistent across specifications. Results also indicate that the association between likelihood of being obese or morbidly obese and the provision of obesity-prevention services is stronger among the low-income population, which is consistent with local health departments' objective of targeting prevention services toward the neediest.

Future studies should include examining the discordance between the local health department jurisdictions and traditional geographic areal units, including spatial analyses, if sufficient study units can be matched. Additional information on resources the local health departments spend on obesity-prevention services might provide opportunities to assess comparative effectiveness and return on investment of various obesity-prevention strategies. Future research should also focus on strengthening the growing evidence on the causal relation between bodyweight and socioeconomic and behavioral factors that also incorporate the social environment in which the individual operates (e.g., school health policies; access to healthy food outlets; and community

parks and bike paths). Such information may be useful in better designing and targeting of public health strategies and policies to maximize impact on obesity and obesity-related behaviors. In addition to the existing and growing evidence from observational studies, innovative experimental and quasi-experimental studies should be explored to provide complementary approaches to assess the causal effects of population health interventions and policies.

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NOTE

1. The threshold is the closest to 200 percent of the poverty line for a family of three (<http://aspe.hhs.gov/poverty/05poverty.shtml>).

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