Understanding the Role of Adolescent Social Networks and Neighborhood Peer Effects on Obesogenic Behaviors and Weight Outcomes using Spatial Analysis

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ABSTRACT

There is an ongoing debate as to the degree to which an adolescent's peer group affects whether they engage in activity that leads to obesity. This paper moves beyond the standard peer effects literature by using spatial econometrics to answer questions on how peers influence adolescent obesity. There have been significant advances in the use of spatial econometrics to estimate peer effects. There are a variety of models that can solve the well-known "reflection problem" that plagues the peer effects literature. This paper furthers the literature by looking at the community contexts of peer effects as well as the school contexts. I specify alternative spatial weight matrices to account for peer effects in the school environment and peer effects in the neighborhood environment. I use data from the National Longitudinal Study on Adolescent Health Survey to answer these questions since it provides the data necessary to estimate spatial models. This is an important study since neighborhood effects can either enhance or detract from school-based policies to combat obesity among youth.

1 INTRODUCTION

Childhood obesity is a serious problem that plagues American youth. Data shows that the percentage of children ages 12 to 19 who are considered obese has increased from 5% in 1980 to 18% in 2010 (Ogden et al, 2012). Obesity in youth can lead to short-run as well as long-run adverse health effects. These adolescents are also subject to social and psychological problems stemming from their weight issues (Crosnoe et al, 2008). This problem has been the subject of much study and scholars have found many reasons for the increases in childhood obesity. Papoutsi et al (2012) find three major factors that can explain the rise in childhood obesity: the environment created by parental work intensity, diet, and food advertising. Larson et al (2013) find that the influence of multiple contexts, including family, peer, and neighborhood contexts, impact childhood obesity.

Recently, the focus of study on childhood obesity has been on the role of peers and their influence of obesity and obesity-related behaviors. Recent studies show that the one's peers have a large impact on obesity (Cunningham et al, 2012). The study of peer effects in health behaviors has flourished because of the realization while individuals make choices based on individual preferences, their decisions can be influenced by others (Blume et al, 2010). While the analysis of peer influence on obesity is well researched, there are noted methodological issues with the estimation of peer effects (Manski, 1993). Many studies on peer effects do not account for these issues and in the studies that try to correct for these issues, most scholars use either school fixed effects or instrumental variable regression techniques to model the endogenous interactions (Fletcher, 2011).

Recent advances in spatial econometrics using social networks have been shown to be an improvement on identification (Lee, Liu, and Lin, 2010). Several authors have used spatial models to improve the study of peer effects on obesity and physical activity. Most studies find moderate to strong effects of weight-related behaviors among a peer group. Schuurman et al (2012) test whether obesity levels and physical activity are clustered using a sample of neighborhoods in Vancouver. They find that there are moderate levels of clustering but these effects are not strong. Chen et al. (2012) estimated a spatial model looking at the role food markets play in adolescent BMI using geo-coded data. The authors find that increasing access to grocery stores and limiting access to fast food restaurants will both significantly lower BMI. In this paper, I apply spatial methodology to estimate the role of peer effects in the school environment and peer effects in the neighborhood environment on obesity and obesity-related behaviors.

2 PEER EFFECTS, PHYSICAL ACTIVITY, AND WEIGHT OUTCOMES

There is an expansive literature that explores the social network effects in obesity and in obesity-related behaviors. Christakis and Fowler (2007) initiated this research by establishing a relationship between peer effects and obesity. However, there has been controversy over the data sample and methodology (Cohen-Cole and Fletcher, 2008). Trogdon et al (2008) find that peer effects exist and are larger for females and adolescents with high BMI. Halliday and Kwak (2009) analyze the methodological issues with estimating peer effects with a focus on the definition of a respondent’s peer group. Auld (2011) finds small social multipliers with obesity, morbid obesity, but not with underweight. Mora and Gil (2012) find strong peer effects using a sample of Spanish adolescents whose social network is defined from classmate nominations. Yang and Huang (2013) find the association with obesity among youth is asymmetric. Weight gain is associated with an increase in obese peers, but this association does not exist with weight loss. There is a general consensus that peer effects do play a role in obesity, but the mechanisms by which they influence obesity need better understanding.

Many researchers have estimated the role that peer effects play in the link between physical activity and weight. Peer effects have been found at all ages from children to college age individuals. Ali et al (2011) find that that peer effects play a role in physical activity, which has implications for adolescent obesity. Carrell et al (2011) find that college peers who had poor fitness levels influence others. Gesell et al (2012) find that increasing activity levels in an afterschool program can boost the activity levels of a child through their immediate social network. Fitzgerald et al (2012) review of adolescent physical activity and their peers. De la Haye et al (2010) find gender based similarities in obesogenic behaviors. Female friends are more likely to engage in screen-time activities while male friends engage in high calorie food consumption. De la Haye et al (2011) find that friends to not only engage in similar behavior but also tend to choose friends based on similar levels of physical activities. This literature shows that interventions geared towards weight-reducing behavior can spread in individual's peer group.

While a major focus of the peer effects literature is on an adolescent's social network, neighborhoods can play a role in individual behavior. Diez-Roux and Mair (2010) explore the role of residential environments on various health outcomes and health inequities. The structural conditions of neighborhoods can play a role in the development of attitudes and norms that can influence the behavior of individuals within those neighborhoods (Galster, 2012). Research on neighborhood effects and obesity focus on the built environment and how home location affect obesity. Neighborhood effects could pick up the fact that people in a community can encourage or discourage positive obesity reducing behavior. Cohen et al (2006) show that increased neighborhood collective efficacy can reduce the probability of obesity risk and overweight. Neighborhood effects can influence weight-related behaviors through a variety of geographic mechanisms (Li et al, 2009; Lopez, 2007; Nelson et al, 2006). However, the study of neighborhood peer effects has not taken advantage of the framework used in social network studies to understand the role of peer effects and obesity. In this paper, I look at the both types of peer effects using a social interactions framework to compare and contrast the different effects of peers on obesity and obesity related behavior.

3 SOCIAL INTERACTION MODELS

Social interaction models study the relationship between interactions among individuals and collective behavior. These models can help explain the observation that individuals within the same group tend to exhibit the same behavior. Akerlof (1997) emphasized the importance of group behavior as a primary driver of individual's choices: "As a consequence, the impact of my choices on my interactions with other members of my social network may be the primary determinant of my decision, with the ordinary determinants of choice of only secondary importance." Social interaction models can be used to identify peer group effects from the data. Peer groups can influence adolescent decision-making through three mechanisms: endogenous interactions, contextual interactions, and correlated effects (Manski, 2000). Endogenous interactions occur when the behavior of the group affects the behavior of the individual, contextual interactions occur when characteristics of the group like age, gender, or race affect the behavior of the individual, and correlated effects occur when the environment plays a role in the behavior of individuals within a group. Several authors have sought to empirically test these interactions and effects, mostly the endogenous interactions (Blume and Durlauf, 2005).

A problem with the estimation of social interaction models is the "reflection" problem (Manski, 1993). While peers' outcome affects the individual's decision, the individual's decision could influence the peers' outcome. In the reduced form of the social interaction framework, the endogenous interactions and the contextual interactions cannot be separated (Durlauf and Ioannides, 2010). The key question in the literature has been how to disentangle these interactions and properly identify the model. The application of spatial econometrics using social networks has been shown to be an improvement on identification (Bramoulle, Djebbari, and Fortin, 2009; Lee, 2007; Lee, Liu, and Lin, 2010). Blume et al (2010) argue, "Social network models provide further focus on the microstructure of interactions among agents and allow for heterogeneity of interactions across pairs of agents." Instead of using peers' means, we are able to explicitly model the interactions between members of the same group. Lin (2010) argues that the spatial autoregressive (SAR) model provides enough information to identify the endogenous and contextual interactions, thus avoiding the reflection problem.

Spatial econometrics provides models for situations where sample data observations are taken with reference to points or regions on a map. Such data often exhibit spatial dependence, as the actions in one region impact those in a neighboring region. The equation for a spatial econometrics model, which takes this impact into account, follows:

(1) $y = \lambda Wy + X\beta + u$,

where y is a function of the neighboring regions' y, and a series of Xs. W represents the spatial weight matrix that quantifies the relationship between the observations. If λ is significantly different from zero, then the data exhibits spatial dependence, indicating that the actions in one region are correlated with those of a neighboring region. There are a variety of methods for specifying the weight matrix W, including using the relationship between observations based on

Euclidean distances (a nearest-neighbors matrix) or assigning values of 1 if regions are adjacent and 0 otherwise (first-order contiguity matrix).

In the social interactions literature, W represents a social network weight matrix where individuals are assigned a 1 if they are in the same peer group and a 0 otherwise. The endogenous peer effect is represented by λ in (1). To fully incorporate all the mechanisms in a social interactions model we outline a generalized version of the Cliff-Ord spatial model that allows for spatial interactions in the dependent variable, explanatory variables, and the disturbances. The empirical specification is given in (2):

(2) $Y = \alpha i + \lambda WY + X\beta + WX\theta + u, \ u=\rho Mu+\epsilon$

In the social interactions framework, the first term (λWy) is the endogenous interaction, the spatially lagged explanatory variables ($WX\theta$) are the contextual interactions, and the spatial interactions in the disturbances (ρMu) are the correlated effects. While the group fixed effects (αi) represent common environmental factors, there may be correlated effects beyond these factors. The spatial interactions on the disturbance also controls for network formation. A positive coefficient denotes that the group forms over similar behavior and a negative coefficient denotes the group does not form over similar behavior. W and M are the weight matrices that specify the relationship between units. In the next section, we describe the data that allows us to estimate the spatial model.

4 DATA

The data is taken from the National Longitudinal Study on Adolescent Health (Add Health). Beginning with an in-school questionnaire administered to a nationally representative sample of students in grades 7 through 12 in 1994-95, the study follows up with a series of in-home interviews of respondents in subsequent years. A unique feature of Add Health is that the first wave contains information on individuals' nominations of their closest friends. Since these friends were also surveyed, this allows us to craft weight matrices based off of this friendship network. The data is taken from the in-home survey of Wave 1. The number of observations in the sample is 12,398.

There are several dependent variables chosen to represent behavior that influences obesity that have been used in the literature (Rees and Sabia, 2010; Ali et al, 2011). The first dependent variable measures the number of times per week the respondent engaged in exercise, sport, or physical activities like rollerblading and biking. This measure is a continuous variable that aggregates the number of times per week the respondent engaged in rollerblading or roller skating, played an active sport like basketball or baseball, and exercised. The next set of dependent variables indicate how many days during the week the individual engages in physical activities and how many days during the week the individual engage in screen-time activities. We also measure the number of hours the respondent watches television or plays video games.

The explanatory variables include basic demographics like age, grade, gender, race and ethnic status. Also included is if the respondent was born in the United States, if they are the first born, the number of siblings, age when they moved to their current home, if they were taught about weight issues in school, and their test score on the Peabody Picture Vocabulary Test (PVT). We include characteristics of the parents like whether they are college educated, whether work full time, their pre-tax income, and if they chose the neighborhood because of the schools. The price of groceries and the price of junk food are included. Contextual data about the community are included like the percent of the block that is urban, median household income, and the percentage that have college degrees. Table 1 gives a summary of the variables.

TABLE 1. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
BMI percentile	22.49	4.42	11.76	63.56
Overweight	0.29	0.46	0	1
Obese	0.22	0.42	0	1
Hours of TV	16.04	14.89	0	99
Exercises	6.74	4.28	0	18
Screen-time (days/wk)	2.36	0.86	0	3
Active (days/wk)	1.43	1.15	0	3
Gender (Male =1)	0.50	0.50	0	1
Age	15.03	1.68	11	19
Grade	9.60	1.61	7	12
Non-Hispanic White	0.58	0.49	0	1
Non-Hispanic Black	0.21	0.40	0	1
Hispanic	0.16	0.36	0	1
Two Biological Parent Household	0.52	0.50	0	1
Parents Work Full-time	0.59	0.49	0	1
Pre-tax Income (000s)	45.76	49.60	0	999
Mom College-Educated	0.26	0.44	0	1
Dad College-Educated	0.22	0.41	0	1
Chose Neighborhood (school)	0.48	0.50	0	1
Age when you moved	8.49	5.69	0	19
Born in the USA	0.74	0.44	0	1
First-born	0.51	0.50	0	1
Number of Siblings	2.35	1.66	0	15
Taught about Weight Issues				
PVT Score	101.10	14.16	13	139
Grocery prices	1.72	0.20	1.44	2.59
Junk food prices	4.16	0.31	3.20	4.94
Percent Urban	0.60	0.48	0	1
Median Household Income	31,743.28	14,453.47	4,999.00	148,752.00
College Educated	0.23	0.14	0	0.86

The table shows that nearly 30% of the sample is overweight and that 22% of that group is considered obese. On average, the respondents engage in less physical activity and more screen-time activities. Half of the sample is male with an average age of 15. Nearly 60% of White, 21% are Black, and 16% is Hispanic. A little over half live in intact households while nearly 60% of the respondents have parents who both work full-time. Average pre-tax income is almost

$46,000. Nearly half of the sample's parents chose the neighborhood because of the schools and for those respondents who moved to their current neighborhood, they moved around the age of eight. Focusing on the contextual measures, the neighborhood is 60% urban, median household income is $31,743, and on average the share of the population that has a college degree is 23%.

5 METHODOLOGY

The procedure estimates the parameters of a cross-sectional spatial autoregressive model with spatial autoregressive disturbances (SARAR). The SARAR model includes the weighted average of the dependent variable and the weighted average of the explanatory variables as right hand side measures as shown as (2):

(2) $Y = \alpha i + \lambda WY + X\beta + WX\theta + u, \; u=\rho Mu+\epsilon$

The SARAR model also allows the error term to depend on the weighted average of errors from other units. The weights on the right-hand side variable and the weight on the errors can be different. The estimator used in this paper, is a generalized spatial two-stage least squares (GS2SLS) estimator of the parameters in the SARAR model[1]. While the spatial parameter on the disturbances accounts for correlated effects, we also include school-level fixed effects in school-grade peer effects model and community-level fixed effects in the neighborhood peer effects model. The fixed effects control for unobservables in the shared environment (Fletcher, 2007).

The estimation procedure is a five-step procedure that uses two-stage least squares (2SLS) residuals to estimate the spatial parameters. Letting X' = [X, WX] and β' = [β, θ], we can rewrite (2) as follows:

(3) $Y = \alpha i + \lambda WY + X'\beta' + u, \; u=\rho Mu+\epsilon$

Simplifying the expression even further by letting Z = [WY, X], we arrive at (4)

[1] The program to run these models is the SPREG command in STATA (Drukker, Prucha, and Raciborski, 2011).

(4) $Y = Z\delta + u,\ u = \rho M u + \epsilon$

Step one in the procedure estimates δ by 2SLS using an instrument matrix H comprised of linearly independent columns (X, WX, W^2X, …, W^qX, MX, M^2X, …,, M^qX). Step two provides an initial GMM estimator of ρ based on 2SLS residuals. This initial estimator is consistent but not efficient, so in step three an efficient GMM estimator of ρ using a weight nonlinear least squares estimator, again based on 2SLS residuals. The G2SSLS estimator of δ is the 2SLS estimator of the transformed model, where we pre-multiply (4) by I – ρM, with Y* = Y – ρMY and Z* = Z – ρMZ, and replacing ρ with the ρ calculated from step three. The final step is to get the efficient GMM estimator of ρ based on GS2SLS results.

6 FINDINGS

There are two peer groups used in the specification of the weight matrices. The first matrix comprises of individuals who are in the same grade at the same school (school-grade). The second weight matrix comprises of individuals who live within a similar distance from the school (neighborhood). I create a 10 nearest neighbor matrix, where the peer receives a 1 if they are one of the ten nearest neighbors to the respondent. Table 2 provides the results of the GS2SLS estimation of both school-grade peer effects and neighborhood peer effects on obesity and obesity status. The table reports the coefficients on the spatial parameters[2].

Table 2. GS2SLS Estimation of Peer Effects on Obesity and Obesity Status

Peer Group	Spatial Parameter	BMI Percentile	Overweight	Obese
School-Grade	λ	-0.9677***	-1.0534***	-0.7114***
	ρ	0.4417***	0.4556***	0.5357***
Neighborhood	λ	0.7282***	0.8133***	0.9400***
	ρ	-0.5287***	-0.5083***	-0.7667***

*** - sig. at 1% level; ** - sig. at 5% level

[2] Full results are available upon request.

The results from Table 2 show that the endogenous peer effect is different depending on the peer group definition. The BMI of individuals are negatively affected by the BMI of school-grade peers, while an individual's BMI is positively affected by the BMI of neighborhood peers. Spatial parameter on errors is significant and positive in the school-grade model, but it is significant and negative in the neighborhood model. This signifies that an exogenous shock to one individual will cause moderate changes in the BMI in those in the peer groups.

The next analysis focuses on the role of peer effects on physical activity like sports and exercise and on sedentary activities like watching television or videos. Table 3 provides the results of school-grade peers on physical activity and sedentary activity.

Table 3. GS2SLS Estimation of Peer Effects on Obesogenic Behaviors

Peer Group	Spatial Parameter	Exercise	Active	Screen-time	Hours of TV
School-Grade	λ	-1.1473***	-1.1427***	-0.7999***	-1.0330***
	ρ	0.5483***	0.5845***	0.3493***	0.4864***
Neighborhood	λ	0.8354***	0.8043***	0.8625***	0.8157***
	ρ	-0.6010***	-0.6804***	-0.6253***	-0.5818***

*** - sig. at 1% level; ** - sig. at 5% level

The results are similar to Table 2 where the endogenous peer effect is negative for school-grade peers and positive for neighborhood peers, while the spatial parameter on the disturbances is positive for school-grade peers and negative for neighborhood peers.

7 CONCLUSION

This paper is the first to compare peer effects within the school environment with peer effects in the neighborhood using a spatial approach. The spatial approach to modeling peer effects has become popular over the last few years with the application of spatial econometric models to networks (see Bramoulle, Djebbari, and Fortin (2009), Lee (2007), Lee, Liu, and Lin (2010)). Currently, this approach has been used to study peer effects in education (Calvo-Armengol et al, 2009) and peer effects in crime (Patacchini and Zenou, 2012). This approach has yet to be applied to the study of peer effects and obesity-related behaviors. This paper showed that peer effects exist with obesity-related behaviors.

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