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ABSTRACT

Is Good Health Contagious? The Impact of BMI Environment on Individual BMI*

Increasing trends in obesity have driven policymakers around the US to examine factors associated with lower Body Mass Index (BMI) and improved health. Our research examines the relationship between an individual's health and their environment. Specifically, we examine whether moving to a state with a different statewide average BMI than the state of origin leads to changes in individual BMI. Combining individual data from the 1997 cohort of the National Longitudinal Survey of Youth with state-level data on average BMI from the Centers for Disease Control, we find that individuals experience changes in BMI that move their individual BMI based on the BMI of their destination state relative to their state of origin. The effect is largely due to female moving to states with much higher BMI than their state of origin. These individuals see an increase in their average BMI of approximately 2.5 percent and an increase in the likelihood of being overweight of approximately 9.8 percentage points.

JEL Classification: I1, I12, J61

Keywords: Body Mass Index, peer effects, migration, obesity

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I. Introduction

Dramatic increases in obesity rates in the United States over recent decades have attracted attention from policymakers and the media (Tavernese, 2015; Flegal et al. 2010; Hedley et al., 2004). The level of concern is due, in no small part, to the health implications and costs associated with being overweight and leading a sedentary lifestyle. Individuals classified as obese experience dramatic reductions in life expectancy (Hennekens and Andreotti, 2013). Obesity combined with inactivity is responsible for over 300,000 premature deaths per year in the United States alone (McGinnis and Foege, 1993). By comparison, over the same period, alcohol was responsible for about 100,000 deaths per year and illicit drugs for roughly 20,000. Only tobacco causes more pre-mature deaths in the United States (Chou, Grossman, and Saffer 2004). Obesity-related diseases include serious and life-threatening conditions such as heart disease, stroke and diabetes. In 2008 alone, the medical care costs of obesity were estimated at $85.7 billion, which was 9.1% of the US national health expenditures (Finkelstein et al., 2009). Somewhat more recent estimates that account for weight misreporting and other statistical issues place this estimate as high as $200 billion (Cawley and Meyerhoefer, 2012). Even in the absence of serious health conditions obesity has negative economic consequences. A higher Body Mass Index (BMI) and particularly BMI levels that surpass the obesity cut-off have been found to be associated with decreased earnings and a lower probability of marriage (Averett and Korenman, 1999; Cawley, 2000; Cawley, 2004; Carmalt et al. 2007; Jolliffe 2011)[1].

Previous research has examined contextual influence and the impact of peers on a variety of health-related behaviors. A number of studies have found peer influence and behavioral environment to be important determinants of smoking, alcohol and drug use and adolescent sexual activity (Case and Katz, 1991; Eisenberg, Golberstein, and Whitlock, 2014; Gaviria and Raphael, 2001; Argys and Rees, 2008; Fletcher, 2007; Lundborg, 2006). Additional studies have examined the effect of peers and environment on obesity and weight and weight-related behaviors (Christakis and Fowler, 2007; Cohen-Cole and Fletcher, 2008; Trogdon, Nonnemaker and Pais, 2008; Fowler and Christakis 2009). Many of these studies suggest that the weight and weight-related behaviors of individually-identified friends play some role in altering weight outcomes for adolescents. Though each of these studies attempt to control for the endogeneity of friend choice it is difficult to establish a truly causal relationship between peer behavior and weight-related behavior or outcomes. The most convincing evidence is recent work by Yakusheva,

[1] Body Mass Index (BMI) is the most common measure of weight-for-height. It is calculated as weight in kilometers divided by height squared where height is measured in meters. Clinical indicators for overweight and obesity in terms of BMI are ($25 \leq$ BMI < 30) for overweight (BMI ≥ 30) for obese.

Kapinos and Weiss (2011) and by Yakusheva, Kapinos and Eisenberg (2014), which shows peer influence on BMI for females but not males utilizing variation due to random roommate assignment in college dormitories, focusing on the individual effect within a tight (two-person) social network.

Our purpose is to determine whether a change in the overall health environment (as opposed to changes in close social groups) leads to changes in individual health. We examine changes in health outcomes (BMI in particular) when individuals move to a state with a substantially different BMI environment from their state of origin. There are a number of possible ways to explain an adjustment of individual BMI towards the new state average and if this relationship is causal, then it suggests that improvements in the health/weight environment can have positive multiplier effects on community health.

To examine this question, we use data from the 1997 cohort of the National Longitudinal Survey of Youth (NLSY97) combined with state-level BMI data from the Behavioral Risk Factor Surveillance System (BRFSS) collected by the Centers for Disease Control and Prevention (CDC). We estimate Difference-in-Differences (DD) models comparing BMI changes for individuals who attain college education who moved to states with higher or lower average BMI to their counterparts who moved to a state with a similar average BMI. Our results provide some evidence that moving to a state with a less healthy (heavier) average BMI causes individual BMI to increase – particularly for females. These effects have meaningful health implications; such moves increase the likelihood that females are classified as overweight.

II. Contextual and Peer Effects on Health

A number of studies have empirically examined the effect of peers on individual-level health behaviors and outcomes. The earliest work focused on establishing a link between peers and health-related risky behaviors such as smoking, drinking and drug use and sexual initiation and activity among adolescents. Many studies rely on reports linking friend dyads, often in combination with fixed effects and instrumental variables, and conclude that peer behavior is contributes to adolescent smoking (Kawaguchi, 2004; Ali and Dwyer, 2011) drinking (Ali and Dwyer, 2010;) and sexual activity (Ali and Dwyer, 2009).

To address the problem of the endogenous selection of peers, a handful of studies exploit natural experiments that plausibly result in random assignment of peers. Sacerdote (2001) relies on the room assignments in residence halls during freshman year of college to measure the strength of the positive correlation between roommates' behaviors. Although primarily focused on academic outcomes, he finds a link between a roommate's previous drinking experience and current fraternity membership. A similar strategy is used in work by Eisenberg, Goldberstein and Whitlock (2014) and by Yakusheva, Kapinos and Eisenberg (2014) to demonstrate peer influence in BMI, smoking, and alcohol use. They find no effects for illicit drug use, gambling, and sexual activity. Argys and Rees (2008) examine the impact of older peers at school and in the classroom assigned via state-mandated kindergarten start ages. They find that older peers affect substance use and sexual activity for girls. In an experimental setting, Bot et al. (2005), verify peer effects in alcohol use by college students by assigning drinking partners in bars.

Other research situated in the peer effects literature has used aggregate measures of group behavior at the school or geographic level to examine responses of individuals to average behaviors. Fletcher (2007) finds that sexual activity of teens responds to the average behavior within his or her school. Examining a wider range of outcomes, Gaviria and Raphael (2001) report that school average levels of drinking, smoking and drug use affect similar individual risky behaviors. Though the causality plausibly runs from the group to the individual in these studies, one must be concerned that parents make residential and schooling choices based on their concern for academic and behavioral reputations.

A smaller set of papers have examined the impact of peers on weight outcomes and healthy weight-related behaviors in particular. [2] In an examination of the correlation between group behaviors, Christakis and Fowler (2007) strongly suggested that 'social networks' were largely responsible for the obesity epidemic. Cohen-Cole and Fletcher (2008) point out that their study fails to address problems of shared contextual effects and sorting of friends based on weight-related behaviors and preferences. They first replicate Christakis and Fowler's results and then address the endogeneity concerns. After these adjustments, their findings suggest that the social network effects are slightly smaller and substantially less precisely estimated. As a result, Cohen-Cole and Fletcher suggest that shared environment plays a much more important role in the positive correlation in weight and obesity as compared to the transmission of behaviors via social network. Trogdon, Nonnemaker and Pais (2008) use friend nominations from the National Longitudinal Survey of Adolescent Health to examine peer weight effects. Using school fixed-effects and instrumental variables approaches to address endogeneity

[2] In the clinical literature there are experiments that show that caloric intake is affected by the behavior of one's eating partner. For a review of this literature see Cruwys, Bevelander and Hermans, 2015. For a review of peer effects of body weight, see Cunningham et al. 2012.

concerns, they find a peer transmission effect that is largest for adolescent girls and teens with the highest BMI.[3]

There are a few papers closely related to our question that examine possible weight assimilation among international immigrants. Where average BMI differs substantially between origin and destination countries research tends to show initial weight more closely mimicking that of the country of origin and then gradual assimilation as migrants slowly approach the BMI levels of their destination country. Bates et al. (2008) report similar finding for Latino and Asian immigrants to the US. Antecol and Bedard (2006) examine patterns of health for immigrants to the US and find that female and male immigrants generally converge to American BMIs after migrating to the United States. Their results showed that on average, female immigrants almost completely converge to American BMI levels within approximately ten years after living in the US and males tend to close a third of the gap within fifteen years. The authors add to the previous literature by controlling for differences in cohort quality as well as examining the complexity of different cultural norms.

Several papers examine BMI assimilation for migrants in countries other than the United States. Kirchengast and Schobert (2006) find higher rates of overweight and obesity among adolescents recently migrating from Turkey and Yugoslavia to Austria. Further studies report increased obesity and obesity-related health risks for migrants compared to natives in the Netherlands (Brussaard et al., 2001) and Germany (Bongard et al., 2002). Kennedy, McDonald and Biddle (2006) find a healthy immigrant effect for the recently arrived foreign-born in the United Kingdom in terms of obesity as well as chronic conditions and self-reported health. Averett, Argys and Kohn (2014) also examine BMI patterns for immigrants to the United Kingdom. Their findings suggest an initial 'healthy immigrant' effect and eventual assimilation through increased weight to approach the higher rates of obesity in the UK.

Suggestive of a peer effect, the longer immigrants remain in their new destination the more they may adopt the diet and exercise behaviors and attitudes of their new neighbors (Hao and Kim, 2009; Goel et al., 2004; Sorlie et al., 1993). For immigrants to Canada, the US, and Australia, the adoption of native behaviors results in worse nutritional habits and increases in obesity (Hao and Kim, 2009; Antecol and Bedard, 2006; McDonald and Kennedy 2005; Tremblay et al., 2005; Hauck and Hollingsworth, 2009).

[3] Trogdon and Allaire (2014) demonstrate that in models of BMI and social networks, the structure of the network is often the most important characteristic, making identification of the influence of peers' BMI on one another within a social network difficult to identify.

Immigrants who have strong cultural ties to their home country or live in areas with concentrated ethnic enclaves the adoption of the behaviors of their new country may be slowed (Hao and Kim, 2009; McDonald and Kennedy, 2005).

Studies that attempt to identify causal effects of peers or locational contextual effects often struggle to eliminate other factors that might result in a positive correlation between the behaviors of peers. Manski (1993) describes three of these factors. The first is called the *endogenous effect*. The *causal* effect of one peer on another is exogenous, but empirically one cannot separate which peer is influencing which resulting in an endogenous relationship. The reflection effect in which peers may simultaneously adopt each other's behaviors manifests itself in a reverse causality that results in an upward bias of the causal impact of one peer on another. The second hypothesis is called the *exogenous effect*, wherein similar behaviors of individuals may result from a shared environment. The third hypothesis is called *correlated effects*, in which the behaviors of group members vary in similar ways as individuals sort themselves into homogeneous groups based on their preferences.

This study aims to isolate a causal effect of moving to a new location on BMI. Our empirical strategy involves measuring the change in the average BMI between the state of origin and the post-move destination state. In an alternative model, we compare individuals who move to a healthier state (one with a BMI that is 'substantially' lower than that of the state of origin) and those who move to an unhealthier state (one with a BMI 'substantially' higher than that of the state of origin) with those who move to a state with similar average BMI.[4] To minimize the likelihood that we are observing movers who have chosen their destination based on a preference for a healthy or unhealthy lifestyle, we focus our attention on individuals who move in young adulthood and attend college in their new location.

In the analyses to follow, we use a pre-existing state-level peer health measure (average state BMI at a fixed point in time) to classify states in order to eliminate the possibility that the reflection effect is confounding a causal relationship. In addition, we attempt to minimize the sorting (correlation) effect by examining moves that occur as high school graduates who attend college after a move. Presumably, the choice of destination is motivated mainly by the characteristics of the university as opposed to the BMI characteristics of the state. To the extent that this is true, we can rule out the correlation effect.

[4] 'Substantially' higher or lower average state BMI are alternatively defined as those that are one standard deviation above or below the state of origin and, in an alternative specification those that are one-half standard deviation above or below the state of origin.

Any remaining positive relationship between average state BMI and the behavior of an individual moving to a healthy state is consistent with a causal effect of the new location. A true endogenous peer effect would be observed if, for example, an individual's peers enjoy jogging groups or hiking excursions during the weekends, it is more likely that that individual will also partake in those events. One could imagine a similar scenario for unhealthy behaviors. Our empirical strategy cannot, however, rule out the influence of shared environment. A drop in BMI after moving to a new, healthier state could result from the causal influence of peers or a shared healthy environment that might include weather and natural amenities conducive to outdoor activities, exercise facilities, and healthy eating options. The purpose of this study is to determine if there is a beneficial (or detrimental) effect of moving to a healthier (or less healthy) state. The combination of these two effects represents the causal effect of moving to a new state on individual BMI. Future work would be necessary to disentangle these two causal mechanisms.

III. Data Description

To understand the relationship between average state BMI and changes in individual BMI, we utilize data from two sources. The individual-level data for our analysis is longitudinal allowing observation of individuals before and after a move. The National Longitudinal Survey of Youth 1997 (NLSY97) cohort is a nationally representative sample of nearly 9,000 young men and women who were born between 1980 and 1984 and who were between the ages of 12 and 16 at the time the selection for the survey began in 1997.[5] These individual-level data are combined with data from the Behavioral Risk Factor Surveillance System (BRFSS) collected by the Centers for Disease Control and Prevention (CDC) that is used to calculate state BMI averages.[6]

The NLSY97 data are well-suited to our analysis in that respondents provide information on their personal and family background as well as annual reports of weight and height, residential location, educational attainment, school enrollment status, family structure, and self-rated health status. Our sample consists of individuals we observe between the ages of 17 and 26 who provide usable reports of height, weight and residential location. Annual reports of height and weight are used to construct measurement-error adjusted BMI (weight in kilograms divided by height in meters squared) for each individual by year.[7] Outliers are excluded from the sample if they are considered extremely underweight (individuals with an implausibly low BMI less than 10) and exceedingly overweight

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[5] These analyses are conducted with restricted access to Bureau of Labor Statistics (BLS) data. For information on obtaining NLSY97 geocode data from the BLS see https://www.bls.gov/nls/nlsgeo97.htm .
[6] BRFSS data are available at https://www.cdc.gov/brfss/data_documentation/index.htm
[7] We apply the Cawley (2004) adjustment to BMI calculations using self-reported height and weight data.

individuals (with BMI greater than 60). We omit respondents with missing values for weight, and those who did not attend college. This leaves us with a sample size of 62,226 person-year observations between 1997 and 2007 prior to imposing any restrictions on types of individual migration.

In order to measure exposure to average state BMI, the NLSY97 data are linked by annual state-of-residence indicators to state-level average BMI measures calculated from multi-year cross-sectional data from the Behavioral Risk Factor Surveillance System (BRFSS) collected by the Centers for Disease Control and Prevention (CDC). The BRFSS provides information on risk factors such smoking, alcohol consumption, height and weight, levels of physical activity and other health-related factors. In our research, we use the weight and height questionnaire section to calculate average BMI levels by state annually. For the purposes of our research, each state is assigned its average BRFSS-calculated BMI. To control for the upward trend in BMI levels over time, we use data from the year 2000 as the base year in which to assign state BMI levels. Because the mean age of our sample was 17.9 during this year, 2000 represents the year in which the typical respondent in the sample would be making decisions regarding college attendance.

Figure 1. Average BMI in the United States

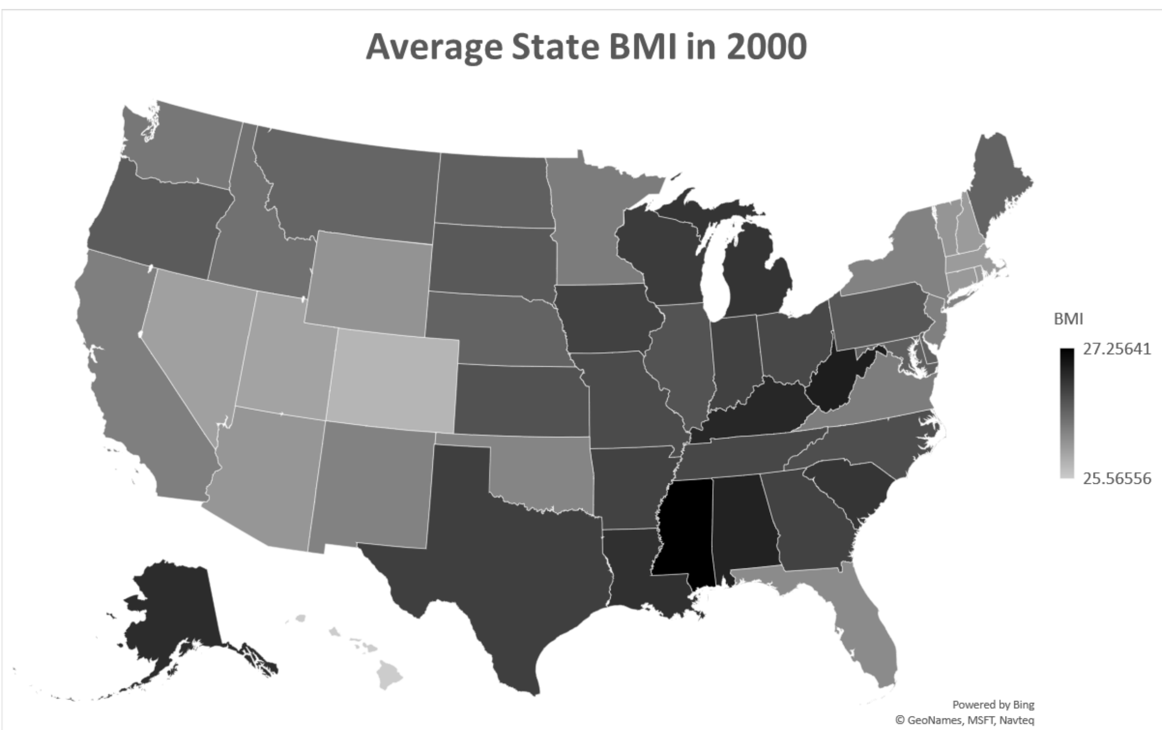
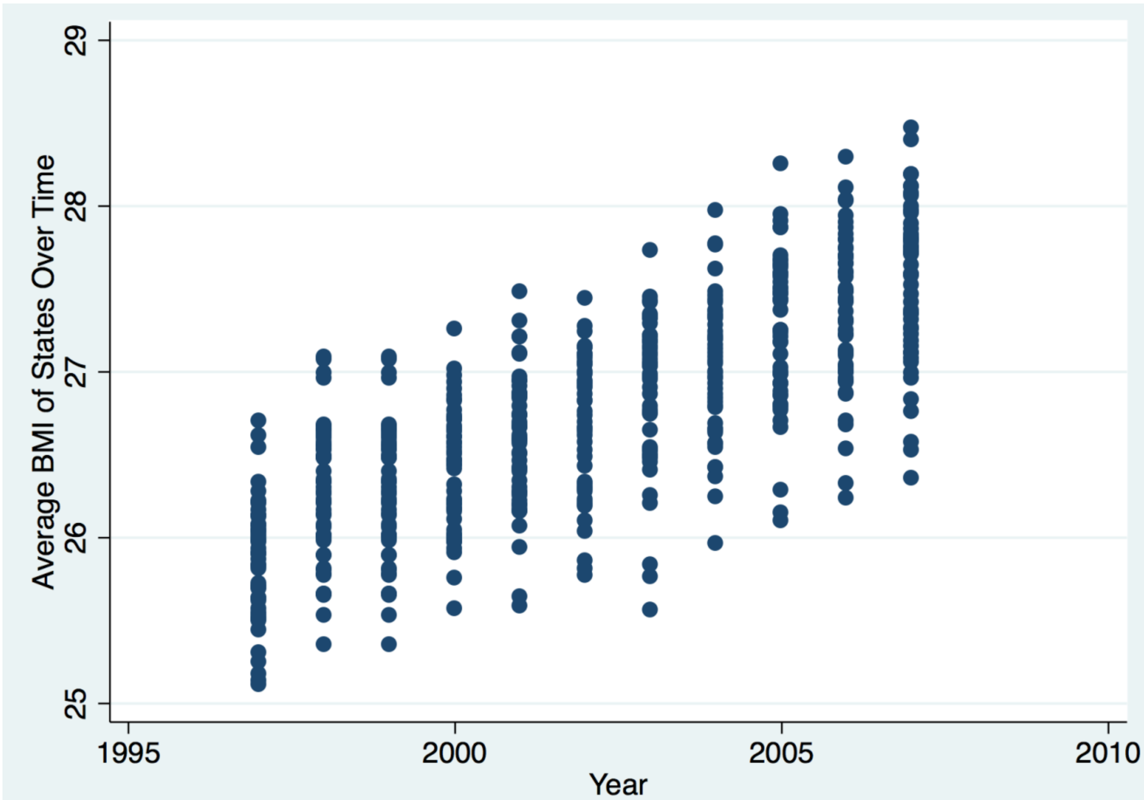


Figure 1 shows geographic distribution of average BMI measures across the US in 2000 and reveals the clear regional variation in average state BMI. States in the southern and mid-western regions of the country have, on average, higher average BMI than western, mountain and northeastern states. Although in our analyses we use average state BMI levels at a point in time (2000), Figure 2 shows average BMI for states in each year between 1997 and 2007. The dispersion and upward trend in BMI are evident.

Figure 2. Distribution of Average BMI of States over Time



Because our empirical strategy is to use longitudinal data to observe individuals pre- and post-move, each individual contributes one observation to our full analysis sample in each year that they report the necessary information between 1997 and 2007 as long as s/he was between the ages of 17 and 26. Because weight trajectories and peer influences differ by gender (Kanter and Caballero, 2012; Argys and Rees, 2008; Trogden, Nonnemaker and Pais, 2008; Antecol and Bedard, 2006), we conduct our analyses (and therefore report means) separately for females (panel 1A) and males (panel 1B).

Table 1A. Sample Means by Move History and Education -- Females age 17 – 20 prior to any move

	All Females	Eventually Attended College	Never Attended College	Eventually Attended College Did not Move	Eventually Attended College Moved Once	Attended College within 3 Years After a Move
BMI	25.15	24.58	26.18	24.72	24.31	24.47
	(5.79)	(5.27)	(6.47)	(5.41)	(4.94)	(4.88)
Overweight⁺	0.31	0.26	0.39	0.28	0.23	0.25
	(0.46)	(0.44)	(0.49)	(0.45)	(0.42)	(0.44)
Obese⁺	0.12	0.10	0.17	0.10	0.08	0.08
	(0.33)	(0.30)	(0.38)	(0.31)	(0.26)	(0.27)
Black⁺	0.27	0.25	0.30	0.26	0.20	0.27
	(0.44)	(0.43)	(0.46)	(0.44)	(0.40)	(0.44)
Hispanic⁺	0.21	0.19	0.26	0.21	0.12	0.12
	(0.41)	(0.39)	(0.44)	(0.41)	(0.33)	(0.33)
White⁺	0.52	0.56	0.44	0.53	0.67	0.61
	(0.50)	(0.50)	(0.50)	(0.50)	(0.47)	(0.49)
Education	11.54	12.02	10.71	12.02	12.03	12.04
	(1.40)	(1.21)	(1.30)	(1.20)	(1.30)	(1.31)
Urban⁺	0.77	0.78	0.77	0.77	0.76	0.77
	(0.42)	(0.42)	(0.42)	(0.42)	(0.43)	(0.42)
Moved After Age 17⁺	0.22	0.24	0.21	0.00	1.00	1.00
	(0.41)	(0.43)	(0.40)	(0.00)	(0.00)	(0.00)
Ever Attended College⁺	0.64	1.00	0.00	1.00	1.00	1.00
	(0.48)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pre-move state BMI					26.46	26.43
					(0.330)	(3.45)
Post-move state BMI					26.39	26.37
					(0.386)	(0.345)
Moved to a Healthier State⁺^					0.182	0.22.0
					(0.386)	(0.414)
Moved to a Unhealthier State⁺^					0.148	0.187
					(0.355)	(0.390)
Person Years	14,043	8,950	5,093	6,774	1,253	490
Individuals	4,052	2,519	1,533	1,851	358	151

Notes: Samples consist of person-years between the ages 17 and 20. Post move years are not included for individuals who moved after the age of 17 and before the age of 20.

⁺ denotes a binary variable;

^ The definition of a move to a 'healthier' state is a move to a new state with an average BMI that is at least one standard deviation (.335) lower than the state of origin. A move to an 'unhealthier' state is a move to a new state with an average BMI that is at least one standard deviation higher than the state of origin.

Table 1B. Sample Means by Move History and Education – Males age 17-20 prior to any move

	All Males	Eventually Attended College	Never Attended College	Eventually Attended College Did not Move	Eventually Attended College Moved Once	Attended College within 3 Years After a Move
BMI	24.59	24.55	24.63	24.71	23.99	24.22
	(5.03)	(4.82)	(5.24)	(4.93)	(4.54)	(4.37)
Overweight⁺	0.37	0.36	0.38	0.38	0.31	0.34
	(0.48)	(0.48)	(0.49)	(0.49)	(0.46)	(0.47)
Obese⁺	0.12	0.11	0.13	0.12	0.08	0.08
	(0.33)	(0.32)	(0.33)	(0.33)	(0.28)	(0.28)
Black⁺	0.25	0.19	0.32	0.20	0.13	0.15
	(0.43)	(0.40)	(0.47)	(0.40)	(0.33)	(0.36)
Hispanic⁺	0.21	0.19	0.24	0.21	0.15	0.17
	(0.41)	(0.39)	(0.43)	(0.40)	(0.35)	(0.37)
White⁺	0.53	0.62	0.44	0.59	0.73	0.67
	(0.50)	(0.49)	(0.50)	(0.49)	(0.45)	(0.47)
Education	11.26	11.88	10.59	11.87	11.95	11.90
	(1.41)	(1.22)	(1.29)	(1.94)	(2.08)	(1.15)
Urban⁺	0.76	0.77	0.74	0.77	0.77	0.80
	(0.43)	(0.42)	(0.44)	(0.42)	(0.42)	(0.40)
Moved After Age	0.21	0.26	0.17	0.00	1.00	1.00
17⁺	(0.41)	(0.44)	(0.37)	(0.00)	(0.00)	(0.00)
Ever Attended	0.52	1.00	0.00	1.00	1.00	1.00
College⁺	(0.50)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pre-move state					26.44	26.47
BMI					(0.334)	(.291)
Post-move state					26.34	26.39
BMI					(0.332)	(.345)
Moved to a					0.194	0.182
Healthier State⁺^					(0.396)	(0.386)
Moved to an					0.132	0.148
Unhealthier State⁺^					(0.339)	(0.355)
Person-years	14,600	7,588	7,012	5,636	1,088	414
Unique individuals	4,288	2,133	2,155	1,543	313	128

Notes: Samples consist of person-years between the ages 17 and 20. Post move years are not included for individuals who moved after the age of 17 and before the age of 20.

⁺ denotes a binary variable;

^ The definition of a move to a 'healthier' state is a move to a new state with an average BMI that is at least one standard deviation (.335) lower than the state of origin. A move to an 'unhealthier' state is a move to a new state with an average BMI that is at least one standard deviation higher than the state of origin.

Table 1 is intended to allow comparison across samples before any respondents move to a new location. Therefore, the sample is restricted to person-year observations prior to any moves (if a move occurred) up to the age of 20. The average BMI for those observed for the full, pre-move sample is 25.15 BMI points for women and 24.59 for men. According to the World Health Organization, for individuals over the age of 20, BMI values under 18.5 are classified as underweight. BMIs ranging from 18.5 to 25 correspond to healthy status. Values ranging from 25 to 30 are considered overweight, and measurements over 30 classify individuals as obese. Thirty-one percent of women and 37 percent of men between the ages of 17 and 20 are overweight and 12 percent of both the female and male samples are obese.

Our strategy to identify moves that are plausibly exogenous to the BMI environment of the destination state focuses on young adults who move as the result of a decision to attend college. We restrict our overall sample to individuals who moved after the age of 17 and who attend some college. This sample is shown in column 5. To best capture identify individuals whose move was motivated by college attendance the most appropriate sample for this analyses are individuals who move after the age of 17, who attend some college, and are enrolled within three years of their move (column 6). We report means for our preferred estimation samples and, for comparison, we report means for a sample of all individuals regardless of education or move status (column 1), all college-educated individuals (column 2), non-college educated individuals (column 3) and college-educated non-movers (column 4).

There are noticeable differences in average BMI by sex; the average BMI for our female sample is nearly one BMI point higher than for the male sample. There is also a striking education gradient in BMI for women. The average BMI for women who eventually attended college (by age 28) is 24.58 as compared to 26.18 for their less-educated counterparts. This pattern is not surprising since education and BMI levels have been shown to have a negative correlation in previous research, with more educated individuals having a lower likelihood of obesity (Devaux, et al. 2011). There are only small differences in BMI by education for males in panel B. Among the college-educated, there is little variation by move status for either women or men.

For comparisons across samples, other characteristics are shown in Table 1. African-Americans comprise approximately one-quarter of all respondents while Hispanics are a just over 20% of the sample. Each individual in our restricted sample has completed some college. In keeping with gender patterns of higher education, 64 percent of the full female sample and 52 percent of the full male sample completed some college. African-American and Hispanic respondents are less likely to appear in the college-educated sample, and, conditional on college education, are substantially less likely to move between states.

Summing up, in order to minimize potential selection bias introduced by movers who select their destination based on preferences for health and weight environment, our analysis focuses on individuals who move as part of their transition to college. Using data from the National Longitudinal Survey of Youth 1997 cohort, we focus our analyses on individuals who move between the ages of 17 and 25 and who attend college in their new location. We measure the individual's BMI in every year, both before and after the move. As seen in column 1 (the full sample that includes non-movers), over 20% of the male and female samples moved between the ages of 17 and 25. Among college-educated movers, in columns 5 and 6, the state BMI average of the origin and destination states across our sample of movers are nearly identical as measured by the 2000 average BMI calculated from the BRFSS. One-third of the college-educated movers move to a state with a substantially different average BMI from their state of origin; 18.2 percent of female college-educated movers moved to a healthier state defined as one in which the average BMI is at least one standard deviation below the national average.[8] Similarly, 14.8 percent of college-educated female movers moved to a state classified as less healthy than their state of origin by this definition.

IV. Methods

We use an individual-level difference-in-differences approach to study the effect of changing peer groups on the BMI of an individual. This analytic approach compares changes in individual BMI after moving to a state with an average state BMI that differs from the state of origin. The first difference removes any effects that are constant before and after the move, including time-invariant individual characteristics such as race and family background. The second difference yields the difference in BMI growth (or loss) resulting from a move to a state with a higher or lower BMI compared to those moving to a state with a similar BMI., Our coefficient of interest identifies the effect of changing peer groups on individual BMI.

Several models of the following form are estimated using ordinary least squares (OLS) with a focus on δ_1, the DD estimator,

$$\ln(BMI)_{ispt} = \alpha + \beta_1 Post_{it} + \delta_1 Change\ in\ StateBMI_{ip} \cdot Post_t + \boldsymbol{\theta_t} + \boldsymbol{\pi_s} + \boldsymbol{\rho_i} + \varepsilon_{ispt} \qquad (1)$$

[8] The standard deviation for average BMI across states is 0.364.

Where the dependent variable $\ln(BMI)_{ispt}$ indicates the natural log of the BMI of individual *i* measured during year *t* while living in state *s*, this individual makes a move between the order specific (from and to) pair of states *p* at some point in the sample. $Post_t$ takes on the value 1 if the year of the observation (t) is after the move. $Change\ in\ StateBMI_{ip}$ is the standardized difference in the 2000 average BMI of the state (to which individual *i* moved) compared to the pre-move state of residence, as such it is indexed not by the current state of residence *s*, but by the move-order specific state pair *p*. θ_t is a vector of year fixed effects, $\boldsymbol{\pi_s}$ is a vector of state fixed effects by state of residence at time t, $\boldsymbol{\rho_i}$ represents individual-specific fixed effects and ε_{ispt} is a normally distributed random error term.

To better understand the impact of changes in one's BMI environment on individual BMI, we specify alternative models that provide estimates of the impact of large changes, over a specified threshold, in average State BMI as the result of a move. Specifically, we estimate:

$$\ln(BMI)_{ispt} = \alpha + \beta_1 Post_{it} + \delta_1 HealthierState_{ip} \cdot Post_{it} + \delta_2 UnhealthierState_{ip} \cdot Post_{it} + \boldsymbol{\theta_t} + \boldsymbol{\pi_s} + \boldsymbol{\rho_i} + \varepsilon_{ispt} \qquad (2)$$

In this specification, the binary variable $HealthierState_{ip}$ indicates that person *i* moved to a relatively healthier state than their state of origin, and the binary variable $Unhealthy_{ip}$ indicates that person *i* moved to a relatively less healthy state. We define the variables $HealthierState_{ip}$ and $UnhealthierState_{ip}$ in two ways. First, $HealthierState_{ip}$ (and $UnhealthierState_{ip}$) are categorized as moving to a state with an average BMI that is at least 1.0 standard deviation in the distribution of time-invariant state BMIs higher (lower) than the state of origin. In a second specification, the $HealthierState_{ip}$ or $UnhealthierState_{ip}$ cutoff is 0.5 standard deviations. As above, $Post_t$ takes on the value one in any survey year after the individual's move. The model in equation (2) also includes state of current residence, year and individual fixed effects.

We estimate this general model for two sub-populations of the NLSY. First, we estimate the model for the sample of movers who have completed some college by their final post-move survey and moved after the age of 17, then, to better identify those who move to attend college, on the sample of movers after age 17 who were enrolled in school within three years of their move. In all cases, models are estimated separately for males and females.

Care needs to be taken with the interpretation of the difference-in-differences variable in our model. Usually one would test for divergent trends in the pre-treatment period to ensure that the difference-in-differences model reports the average effect of treatment – attributing all of the effect to gaining treatment status. In our situation, parallel pre-period trends seem unlikely, as individuals in states with higher average BMI could have differential BMI growth paths than those in states with lower average BMI. This means that we cannot wholly attribute any results to the effect of treatment, instead our estimator should be thought of as the total effect of changing peer groups. We cannot determine whether any estimated effects are due to gaining a new set of peers or due to the loss of the old set of peers. However, any clinical implications of a result are unaltered by this methodological weakness. For example if we find that a change to a healthier state results in BMI loss, then whether this is due to gaining healthy peers and context or losing unhealthy peers and context is irrelevant to the overall health outcome of lower BMI.

The result of estimating the models laid out in equations (1) and (2) provide insight into how changes in peer groups alter BMI levels throughout the young adult population of movers. Over much of the BMI distribution, changes in BMI have little impact on overall health and disease. Of more concern, is whether changes in BMI influenced by peers have important impacts on health. We estimate the following models:

$$O_{ispt} = \alpha + \beta_1 Post_{it} + \delta_1 Change\ in\ StateBMI_{ip} \cdot Post_{it} + \boldsymbol{\theta_t} + \boldsymbol{\pi_s} + \boldsymbol{\rho_i} + \varepsilon_{ispt} \qquad (3)$$

and

$$O_{ispt} = \alpha + \beta_1 Post_{it} + \delta_1 HealthierState_{ip} \cdot Post_{it} + \delta_2 UnhealthierState_{ip} \cdot Post_{it} + \boldsymbol{\theta_t} + \boldsymbol{\pi_s} + \boldsymbol{\rho_i} + \varepsilon_{ispt} \qquad (4)$$

Where dependent variables representing individual BMI in equations (1) and (2) are replaced with a dichotomous indicator that an individual's BMI exceeding the overweight (BMI > 25) threshold. We do not run these models on a binary outcome variable for individuals being obese (BMI > 30) due to a small number of observations in which individuals who are at some point obese move to states with differing average BMI.[9] Models (3) and (4) are estimated as linear probability models.

IV. Results

Estimates from equations (1) and (2) are reported in Table 2 for college-educated movers using individual BMI as the dependent variable. Each column reports results from a regression on a different measure of change in state BMI. Results for females appear in columns 1-3 and for males in columns 4-6. Estimates of the parameter β_1 are reported in row 1. δ_1 (and δ_2), the difference-in-difference estimators are reported in the next rows of the table. Standard errors are adjusted for clustering at the individual level.

Across all models in Table 2 it is clear that females and males respond differently to exposure to changes in average BMI after a move. One example of these differential responses can be seen in the estimates of the parameter β_1. Although not the main focus of our models, these estimates indicate that although there is no discernable overall post-move pattern for women, college-educated men experience a reduction in their individual BMI of one percent in the aftermath of any move, although this effect is largest and significant only in the model that controls for moves to states with an average BMI one standard deviation higher or lower. In contrast, women appear more responsive to the BMI environment in their new location. Estimates of equation (1), reported in columns 1 and 4, suggest that women are more likely to assimilate toward average BMI levels. Estimates of parameter δ_1, reported in row 2, are positive for both women and men. This suggests that as the difference between average BMI in an individual's pre-move and post-move states grows, there is a larger post-move increase in BMI. The effect of the destination average BMI is relatively large (but not significant) for women.

[9] There are under 10 individuals contributing such observations.

Table 2. Difference in Difference Model: The Effect of State average BMI on the Individual Log BMI of Movers who Attained Some College.

	Females			Males		
	logBMI	logBMI	logBMI	logBMI	logBMI	logBMI
Post move	0.0002 (0.0055)	-0.0039 (0.0065)	-0.0002 (0.0069)	-0.0081 (0.0111)	-0.0111* (0.0062)	-0.0093 (0.0066)
Post move * Change in State BMI	0.0183 (0.0121)			0.0008 (0.0111)		
Post move to a Healthier State (> 1 standard deviation)		-0.0055 (0.0117)			0.0103 (0.0104)	
Post move to an Unhealthier State (> 1 standard deviation)		0.0245* (0.0136)			0.0040 (0.0113)	
Post move to a Healthier State (> .5 standard deviation)			-0.0083 (0.0119)			0.0088 (0.0107)
Post move to an Unhealthier State (> .5 standard deviation)			0.0039 (0.0115)			-0.0033 (0.0096)
Sample size	5,428	5,428	5,428	4,737	4,737	4,737

Notes: Sample consists of individuals between the ages of 17 and 26 who moved at least once after the age of 17 and who attained some college education by their final interview before age 26. All models include year, state and individual fixed effects.
*, **, and *** represent $p < 0.1$, $p < 0.05$, and $p < 0.01$ respectively.

We explore whether there is evidence of a non-linear effect across levels of average state BMI with estimates of equation (2) presented in rows 2 and 3 in Table 2 for women (and rows 5 and 6 for men). First, we replace the linear measure of average state BMI with the dichotomous indicator that the post-move state BMI is lower than that of the individual's pre-move state by at least one standard deviation ($HealthierState_{is}$).[10] Similarly, the dichotomous variable, $UnhealthierState_{is}$, indicates that the post-state BMI is higher than that of the pre-move state by more than one standard deviation. These results, reported in columns 2 and 5, suggest that women who move to a less healthy state experience a BMI increase of nearly 2.5 percent. The effect on women of moving to a healthier state is negative, but smaller and not precisely estimated. As with the linear model, there is no significant effect for males. In

[10] As noted above, the standard deviation in average State BMI is .0.364.

columns 3 and 6, we explore whether smaller changes in state-level BMI have any effect on individual BMI by examining moves to states that are healthier or less healthy than the state of origin by a narrower margin, only 0.5 standard deviation. In these models, we find that the direction of the effect for women is still consistent with the hypothesized peer effect, but not precisely estimated in either direction. As before, is no significant effect of the new BMI environment for males.

Table 3. Difference in Difference coefficients – the effect of State average BMI on the probability of overweight (BMI > 25) of movers who attain some college.

	Females			Males		
	BMI>25	BMI>25	BMI>25	BMI>25	BMI>25	BMI>25
Post move	0.0092 (0.0175)	-0.0093 (0.0199)	-0.0036 (0.0213)	-0.0319 (0.0194)	- 0.0506** (0.0227)	-0.0537* (0.0239)
Post move * Change in State BMI	0.0825** (0.0359)			-0.0451 (0.0388)		
Post move to a Healthier State (> 1 standard deviation)		-0.0145 (0.0347)			0.0941** (0.0418)	
Post move to an Unhealthier State (> 1 standard deviation)		0.0977** (0.0401)			0.0239 (0.0462)	
Post move to a Healthier State (> .5 standard deviation)			-0.0182 (0.0351)			0.0971** (0.0427)
Post move to an Unhealthier State (> .5 standard deviation)			0.0422 (0.0331)			0.0232 (0.0387)
Sample size	5,428	5,428	5,428	4,737	4,737	4,737

Notes: Sample consists of individuals between the ages of 17 and 26 who moved at least once after the age of 17 and who attained some college education by their final interview before age 26. All models include year state, and individual fixed effects.
*, **, and *** represent p < 0.1, p < 0.05, and p < 0.01 respectively.

Having established, at least for females that there is some relationship between individual BMI and the change in the BMI environment, we estimate further models to understand if these BMI changes are meaningful. Categorization of individuals as overweight has been a useful metric linked to increasing health risks. Estimates of equation (2), in which a dichotomous indicator for being overweight is the dependent variables, are reported in Table 3.

The models in Table 3 suggest that the changes in individual BMI experienced by women moving to healthier and unhealthier states shown in Table 2 result in changes that can have a meaningful impact on women's health. As shown in column 1, the move to a state with an average BMI that is one standard deviation higher results in an increase in the probability of moving into the overweight range. Estimates in column 2 suggest that this change is driven by an increase in overweight status of women moving to substantially unhealthier states (an increase in state BMI of more than 1 standard deviation.) There is no significant response for women who experience an increase or decrease of at least 0.5 standard deviations in average BMI (column 3). For men, in columns 4-6 we find an unexpected result. As they move to states with lower average BMI, their probability of being classified as overweight increases. This could be the paradoxical effect of muscular men having a BMI that rises above 25. As they move to a healthier state, the new environment may promote increased fitness and muscle mass resulting in a higher BMI. This possible explanation is supported by recent work by Tomiyama et al. (2016), who show that BMI can often classify individuals as overweight, when other measures of cardio-metabolic health would indicate that individual is healthy.[11] These errors in classification found by Tomiyama et al. (2016) were more likely to occur in males than females. We however cannot rule out the possibility that moves to healthier states has a perverse effect on diet and exercise behaviors, creating worse BMI outcomes for males.

The motivation for our identification strategy was to examine moves that were unlikely to be motivated by the health status of the destination state by examining moves to a new state made at the time of college attendance. Although the sample in the estimates shown in tables 2-4 include individuals who moved between the ages of 17 and 25 and had attended college, the sample selection criteria did not closely link the move to college attendance. We re-estimate equations (1) and (2) to measure the effect of moving on individual BMI (Table 4), likelihood of overweight (Table 5) on a more select sample. In this instance we restrict our sample to individuals who completed some college, who moved only once between the ages of 17 and 25 and who were enrolled in school within three years of their move. The results for this sample look very similar to the results for the larger sample. As seen in tables 5 and 6,

[11] The other measures of cardio-metabolic health were blood pressure, triglyceride, cholesterol and glucose levels, insulin resistance and C-reactive protein.

women who moved to a less healthy state experienced a significant increase in their BMI and a greater likelihood of being classified as overweight. The results for males who were enrolled in school soon after their move still exhibit evidence that a move to a healthier state is associated with a higher probability of having a BMI in excess of 25 and therefore being classified as overweight.

Table 4. Difference in Difference coefficients – the effect of State average log BMI on the individual log BMI of movers who attended college within 3 years of their move.

	Females			Males		
	logBMI	logBMI	logBMI	logBMI	logBMI	logBMI
Post move	0.0024 (0.0065)	-0.0037 (0.0081)	-0.0016 (0.0087)	-0.0068 (0.0073)	-0.0064 (0.0086)	-0.0063 (0.0144)
Post move * Change in State BMI	0.0180 (0.0147)			0.0032 (0.0110)		
Post move to a Healthier State (> 1 standard deviation)		-0.0019 (0.0153)			0.0007 (0.0139)	
Post move to an Unhealthier State (> 1 standard deviation)		0.0290* (0.0159)			-0.0050 (0.0122)	
Post move to a Healthier State (> .5 standard deviation)			-0.0035 (0.0156)			0.0006 (0.0144)
Post move to an Unhealthier State (> .5 standard deviation)			0.0133 (0.0140)			-0.0030 (0.0115)
Sample size	2,810	2,810	2,810	2,286	2,286	2,286

Notes: Sample consists of individuals between the ages of 17 and 26 who moved at least once after the age of 17 and attended college within 3 years after their move. All models include year, state and individual fixed effects.
*, **, and *** represent $p < 0.1$, $p < 0.05$, and $p < 0.01$ respectively.

Table 5. Difference in Difference coefficients – the effect of State average BMI on the probability of overweight (BMI > 25) of movers who attended college within 3 years of their move.

	Females			Males		
	BMI>25	BMI>25	BMI>25	BMI>25	BMI>25	BMI>25
Post move	-0.0024 (0.0223)	-0.0298 (0.0247)	-0.0242 (0.0257)	-0.0316 (0.0258)	-0.0393 (0.0308)	-0.0538* (0.0318)
Post move * Change in State BMI	0.0917** (0.0450)			-0.0502 (0.0532)		
Post move to a Healthier State (> 1 standard deviation)		-0.0080 (0.0435)			0.0765 (0.0549)	
Post move to an Unhealthier State (> 1 standard deviation)		0.1273*** (0.0485)			-0.0313 (0.0651)	
Post move to a Healthier State (> .5 standard deviation)			-0.0120 (0.0441)			0.0897 (0.0559)
Post move to an Unhealthier State (> .5 standard deviation)			0.0671* (0.0399)			0.0265 (0.0535)
Sample size	2,810	2,810	2,810	2,286	2,286	2,286

Notes: Sample consists of individuals between the ages of 17 and 26 who moved at least once after the age of 17 and were enrolled in school within 3 years after their move. All models include year, state and individual fixed effects.
*, **, and *** represent $p < 0.1$, $p < 0.05$, and $p < 0.01$ respectively.

V. Conclusion

As part of the ongoing discussion around factors contributing to obesity, our research aims to explain the relationship between an individual's BMI and their 'health' environment. We estimate difference-in-differences models that compare BMI changes after moving to states with substantially higher (or lower) BMI levels than the state of origin. Combining individual data from the 1997 cohort of the National Longitudinal Survey of Youth with state-level data on average BMI from the Centers for Disease Control, we find that women experience changes in BMI that move toward the average health level of their destination state although the magnitude and timing of these effects vary by outcome and treatment group.

By examining moves for young adults transitioning to college, our strategy is to examine moves in which location choice is motivated by academic and financial decisions rather than preferences for a healthy environment. When restricting our sample only to students and comparing student movers experiencing a BMI change to students who do not move and to students who move to a state with similar BMI, we find patterns consistent with peer influence. Female students moving to unhealthy states see sizable increases in BMI and the probability of being overweight. We find somewhat unexpected results for men. Male students experience increased BMI of similar magnitude after a move to a healthy state. Finding larger, and more consistent effects for women is not entirely surprising and is in keeping with other studies that find stronger peer effects for females (Antecol and Bedard, 2006; Argys and Rees, 2008; Trogdon, Nonnemaker and Pais, 2008; Yakusheva, Kapinos, and Eisenberg, 2014).

Though our approach rules out many, possibly endogenous, explanations for these changes in BMI, whether the effects are the result of peer influence or by a shared environment conducive to healthy living remains to be answered. There is some previous work examining the impact of peers on eating (McFerran et al., 2010) and exercise (Murcia et al., 2008). Additional examination of the post-move changes in behaviors that might contribute to BMI changes could add insight into these patterns.

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