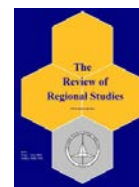




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# Is there a Tradeoff between Remote Living and Healthy Living? The Impact of Remoteness on Body Weight\*

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**Abstract:** Using the 1979 National Longitudinal Survey of Youth (NLSY79), we examine the relationship between Body Mass Index (BMI) and the remoteness of the county in which the individual lives. Remoteness in this study is identified by calculating the geographical position of the county with respect to metropolitan areas of different sizes (urban hierarchy) of the location. Since BMI affects where an individual chooses to live, there may be endogeneity bias. To address this concern, we identify patterns of mobility in which the choice of location is independent of BMI. In a framework that accounts for unobserved individual-level heterogeneity and sources of endogeneity bias, we show that after controlling for urban sprawl or location density, there is no systematic manner through which remoteness affects body weight.

**Keywords:** urban hierarchy, distance, body mass index (BMI)

**JEL Codes:** I12; R14; R12

## I. INTRODUCTION

The lifestyle of an individual is influenced by different individual factors, including attitudes, beliefs, and knowledge, as well as environmental factors including the physical, social, political, economic, and media environment. The built environment is one of these factors. The built environment<sup>1</sup> is any element in the physical environment that has been built by humans, including roads, buildings, infrastructure, and parks. The literature demonstrates that the built environment in various settings (schools, daycare centers, workplaces, neighborhoods, etc.) can facilitate, but can also impede, regular physical activity and the adoption of healthy eating by citizens (Gordon-Larsen et al. 2006, Winters et al. 2010, Adlakha 2015).

The dimensions of the environmental factors that could affect the lifestyle choices of individuals we typically think of are the transportation system, land use (i.e., different activities within a given geographical area), and urban design. The two factors that have received the most attention from the academic literature thus far are urban sprawl and land use mix (Duncan et al., 2010; Christian et al., 2013; Wheeler et al., 2010). Moreover, the location of a community may determine the available amenities that are conducive to active lifestyles. Along these lines, rurality has been associated with higher obesity rates and lower activity rates due to distance from

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<sup>1</sup> See the list of definitions in Appendix A.

resources such as gyms and parks (Patterson, 2004; Boehmer et al., 2006; Jilcott et al., 2007). These relationships are not conclusive, however, as a rural area's climate, topographical variation, and proximity to water may cause an individual to lead a more active lifestyle in a rural community. At the same time, the relationship between place characteristics and physical activity may be correlated and may not only act in one direct (i.e., because a person lives in a rural area they are less active). Jokela et al. (2009) suggests that the higher body weight of people living in rural areas of Finland may be due to both self-selection and social causation mechanisms. In other words, heavier people tend to migrate to more rural areas where people tend to get heavier.

The present study adds a new dimension to the relationship between environment and higher body weight that has not received much attention in the literature. Specifically, is an individual's weight status, as measured by BMI, influenced by the remoteness of the county in which he (or she) lives? To answer this question, we employ a multidimensional measure of remoteness that identifies the position of a county within the urban hierarchy (where the hierarchy is based on agglomerative size, e.g., a metropolitan with population of 1.5 million or more is a tier 1 metro, a metropolitan of population between 0.5 million and 1.5 million is a tier 2 metro, and so on). This question considers not only the distance to the nearest urban center (sometimes termed the *urban distance discount*) but also the incremental distances to higher tiers of the urban hierarchy of the location, an aspect the density/sprawl literature does not address.

The previous research has focused primarily on the relationship between urban sprawl and body weight (Ewing et al., 2003; Plantinga and Bernell, 2007b; Eid et al., 2008), which is only one aspect of the geography of a location.<sup>2</sup> The other aspect that we add is the remoteness of a location. This omission has occurred despite the recent wave of research that shows how local outcomes are influenced by the interaction between distance and agglomeration. For example, Partridge et al. (2007, 2008a, b) argue that the costs of access to jobs and urban amenities increase with distance in a way that is different across urban tier. By identifying the position of the county within the urban hierarchy, we are better able to address the potential penalties that would arise from limited access to factors that help reduce an obesogenic environment (hospitals, well-equipped gyms, full-range food stores with healthy food options, parks, recreational facilities, etc.).<sup>3</sup> Distances from metropolitan areas of different tiers are likely determinants of the obesogenic environment of a location over and beyond the connection between body weight and urban density as some of these higher-tiered metros not only offer their residents amenities but also make these amenities available indirectly to residents of nearby communities.

Table 1 illustrates how urban sprawl and remoteness can be different markers for a location. Four pairs of counties are listed in Table 1. Each pair is similar in urban density as measured by three variables: population density, the distance from the population-weighted centroid of

<sup>2</sup> Brueckner (2001) defines urban sprawl as "a spatial growth of cities that is excessive relative to what is socially desirable." This "excessiveness" arises from various market failures: failure to (a) take into account the social value of open space, (b) to recognize the social costs of congestion created by the use of the road network, and (c) to take into account all of the public infrastructure costs generated by the projects (Brueckner, 2000, 2001). An empirical measurement of sprawl entails first identifying the optimal size of each city, accounting for population growth, rising household incomes, (transportation) technological progress, and nonstationary taste parameters, and then evaluating the contributions of the above-mentioned externalities on urban growth beyond this optimal level. We are therefore skeptical of measures of sprawl, which we believe are essentially measures of urban density. Therefore, throughout this paper, we use the terms urban sprawl and urban density interchangeably. For a comprehensive discussion of the practical challenges of calculating a measure of urban sprawl, see Frenkel and Ashkenazi (2008).

<sup>3</sup> See Section II for a detailed discussion of the links between distance and body weight.

**Table 1: Examples of Counties with Similar Urban Sprawl but Positioned within Different Tiers of the Urban Hierarchy and Different Obesity Rates**

<b>Rural (non-metro) county</b>		Low density		High density	
County name		Lamb	Jefferson	Holmes	McDowell
State		TX	WA	OH	NC
Obesity rate		28	22	29	34
Density		14	15	92	96
Population-weighted distance to nearest micropolitan area		49	29	30	37
Incremental distance to nearest metro		18	17	21	16
Incremental distance to nearest 0.25m metro		344	20	0	0
Incremental distance to nearest 0.5m metro		0	0	20	48
Incremental distance to nearest 1.5m metro		107	0	28	195
<b>Metro county</b>		Low density		High density	
County name		San Juan	Yavapai	King	Fayette
State		NM	AZ	WA	KY
Obesity rate		28	20	22	29
Density		21	21	818	918
Population-weighted distance to nearest metropolitan area		0	0	3	2
Incremental distance to nearest metro		0	0	0	0
Incremental distance to nearest 0.25m metro		232	130	0	0
Incremental distance to nearest 0.5m metro		0	0	0	106
Incremental distance to nearest 1.5m metro		206	0	0	22
Name of the nearest metro (population in millions)		Farmington (0.11)	Prescott (0.17)	Seattle (3.04)	Lexington (0.4)
Next hierarchy (population in millions)		Albuquerque (0.73)	Phoenix (3.3)		Louisville (1.2)

Notes: (a) "Population-weighted distance" refers to the distance from the population-weighted centroid of the county to the population-weighted centroid of the respective micropolitan or metropolitan area. (b) 0.25m, 0.5m, and 1.5m refer to quarter, half, and one-and-a-half million populations. (c) All values are for the year 2000. (d) All distances are in kilometers. (e) The obesity rates are the county-level estimates by the Center for Disease Control and Prevention (CDC).

the nearest micropolitan or metropolitan area, and the incremental distance to the nearest metro. Remoteness refers to the position of the county in the urban hierarchy as measured by incremental distances to the nearest metropolitan areas of populations 0.25 million, 0.5 million, and 1.5 million. We see that the counties can be alike in urban sprawl/density but significantly different in terms of remoteness. They also have strikingly different obesity rates.

Answering our research question is difficult because individual-level heterogeneity and self-selection may create endogeneity issues.<sup>4</sup> We address the individual-level heterogeneity problem by estimating a fixed effects model that captures any time-invariant unobserved heterogeneity that could drive both county choice and weight outcomes. It is important to note that this specification is equivalent to the model used by Eid et al. (2008) estimate the impact of urban sprawl on body weight. In our fixed-effects estimations, we find that after controlling for urban sprawl/density, remoteness has an inconsistent influence on an individual's BMI.

To tackle the individual self-selection problem, we estimate the effect of remoteness on BMI in a subsample in which the choice of location is *not* likely to be influenced by BMI. Specifically, we take the sample of individuals who moved back to their childhood county (the county in which they lived at age 14), which we refer to as the returners. Self-selection is likely to be present when the movers with higher body weight choose counties that are systematically more remote (Jokela et al, 2009), perhaps because the remote counties are more conducive to their lifestyle. In the case of returners, this pattern does not seem plausible. First, the drivers of their choice of counties are principally family and network ties, familiarity with the area, and culture (Mills and Hazarika, 2001; Lansing and Barth, 1967) rather than body weight. Second, as we show later, the childhood counties of the returners are *not* systematically different compared to the average county (see Table 3). Thus, we expect the location decisions for the returner sample to *not* be systematically correlated with body weight. Thus, this approach addresses the potential correlation between the error term and the position of the county in the urban hierarchy (our vector of interest).<sup>5</sup>

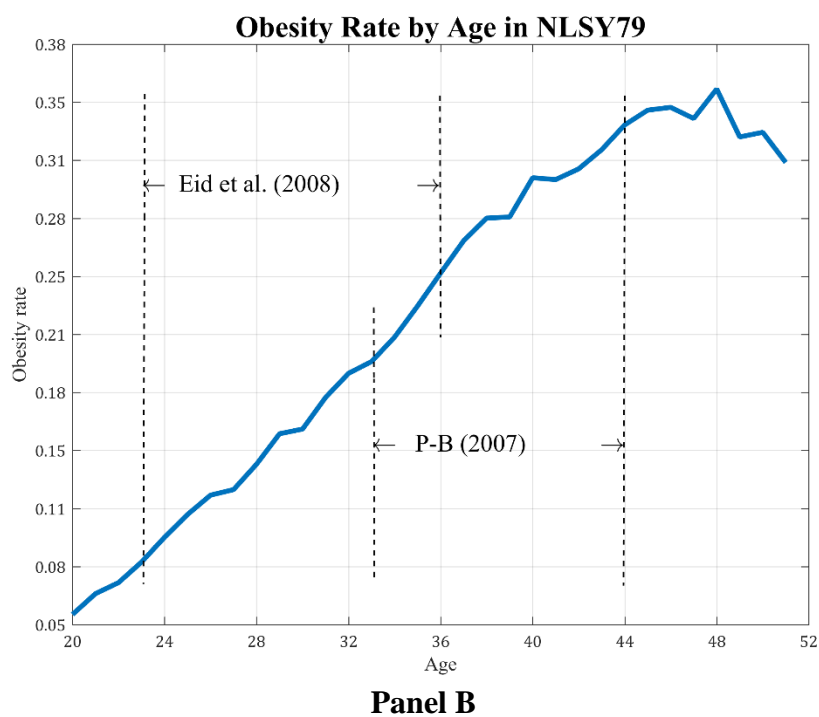
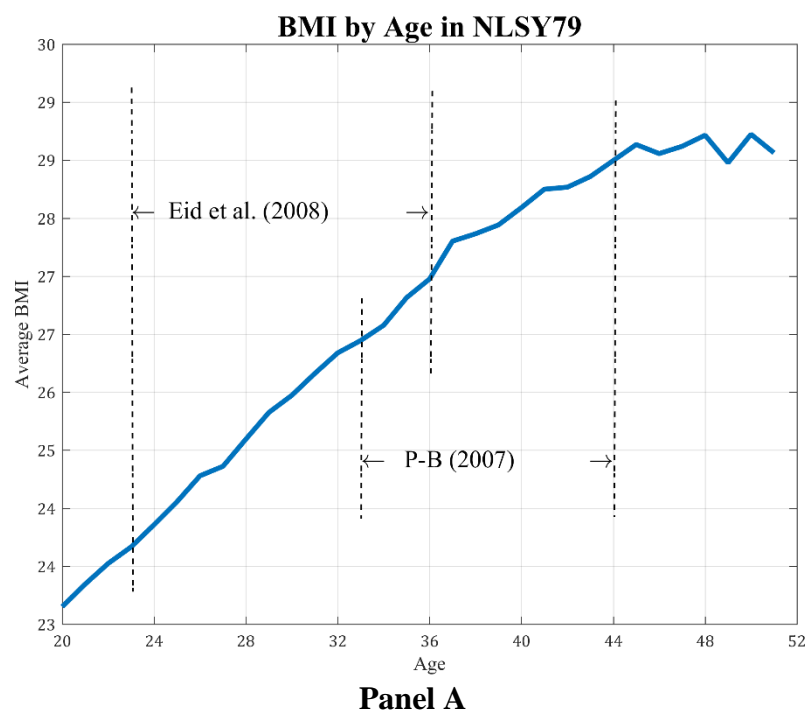
For the subsample of returners, where the choice of location is independent of BMI, we employ an event study approach and utilize the variation in remoteness before and after the move. We show that after controlling for urban sprawl or location density, there is no systematic manner through which remoteness affects body weight. Note that this framework accounts for unobserved individual-level heterogeneity and sources of endogeneity bias.

Our study adds to the literature in a few important ways. First, we are interested in the potential “weight penalties” arising from a county's remoteness from (or proximity to) amenities and services available in higher-tiered metropolitan areas. We agree that how sprawled a location is may also contribute to the obesogenic environment and, therefore, is a confounding factor in the estimation of the effect of remoteness on body weight. We control for urban density by including population density, the distance from the population-weighted centroid of the county to the population weighted centroid of the nearest micropolitan or metropolitan area, and the incremental distance to the nearest metro.<sup>6</sup> In our preferred specification, most of the relationship between our distance increments and weight disappears.

<sup>4</sup> See Eid et al. (2008), Plantinga and Bernell (2007a, 2007b). Section II includes a detailed discussion.

<sup>5</sup> For further discussion, see Section 4.

<sup>6</sup> The measure of urban sprawl in Plantinga and Bernell (2007) comes from Ewing, Pendall, and Chen (2002) and Ewing et al. (2003), where sprawl is defined as “the process in which the spread of development across the landscape far outpaces population.” Eid et al. (2007) use 30-meter resolution remote-sensing land cover data from Burchfield et al. (2006) to measure residential sprawl and counts of retail shops and churches from U.S. County Business Patterns to measure the extent to which a neighborhood can be characterized as *mixed use*.

**Figure 1: BMI and Incidence of Obesity by Age in the Sample: Ages 20–52.**

Secondly, while our findings support those of Eid et al. (2008) in that we generally do not find effects of sprawl on individual BMI, we use an improved sample and methodology. Eid et al. (2008) use an identification strategy that utilizes variation when individuals move. In their sample, while mobility is high (because of a smaller age range), the variation in BMI is relatively low. We use data that covers a longer time period and includes the prime mobility years of the respondents over the entire age range over which individuals gain weight.<sup>7</sup> Our sample, therefore, is more representative of the population. Figure 1 presents the average BMI and the incidence of obesity in our sample, where we allow weight gains to fully unfold and obesity rates to peak.

The other notable existing research on this topic is Plantinga and Bernell (2007b), who estimate a two-equation system with BMI and a binary variable of whether individuals choose to reside in a high- or low-sprawl county as endogenous variables. However, their exclusion restriction does not consider important variables such as marital status and family size from the BMI equation and smoking and region variables from the location choice equation. Zhao and Kaestner (2010) question the validity of these instruments because it is likely that marital status and family size are correlated with BMI. In our analysis, we find that marital status and family size are indeed correlated with BMI.

Finally, one of the important contributions of this paper is that we distinguish between metropolitan and nonmetropolitan counties. Guettabi and Munasib (2014) find that county obesity rate is spatially nonstationary and that there are spatial heterogeneities in how distance affects obesity rates. Partridge et al. (2008a) argue that some of the reasons the effect of distance may vary spatially are initial settlement patterns, the availability and quality of public transportation, and geographic terrain. Land use regulations and zoning practices may also be different in urbanized areas than in rural areas.<sup>8</sup> We divide our samples into metropolitan and nonmetropolitan counties<sup>9</sup> to investigate whether the remoteness issue is unique to a certain type of county. In an analysis of distance from urban centers, excluding nonmetropolitan counties will lead to only a partial picture.

The rest of this paper is organized as follows. We discuss body weight in the context of geographical locations in Section 1, we explain the data in Section 2, we explain the econometric model in Section 3, and we present the results in section 4. Section 5 concludes.

## 2. DATA

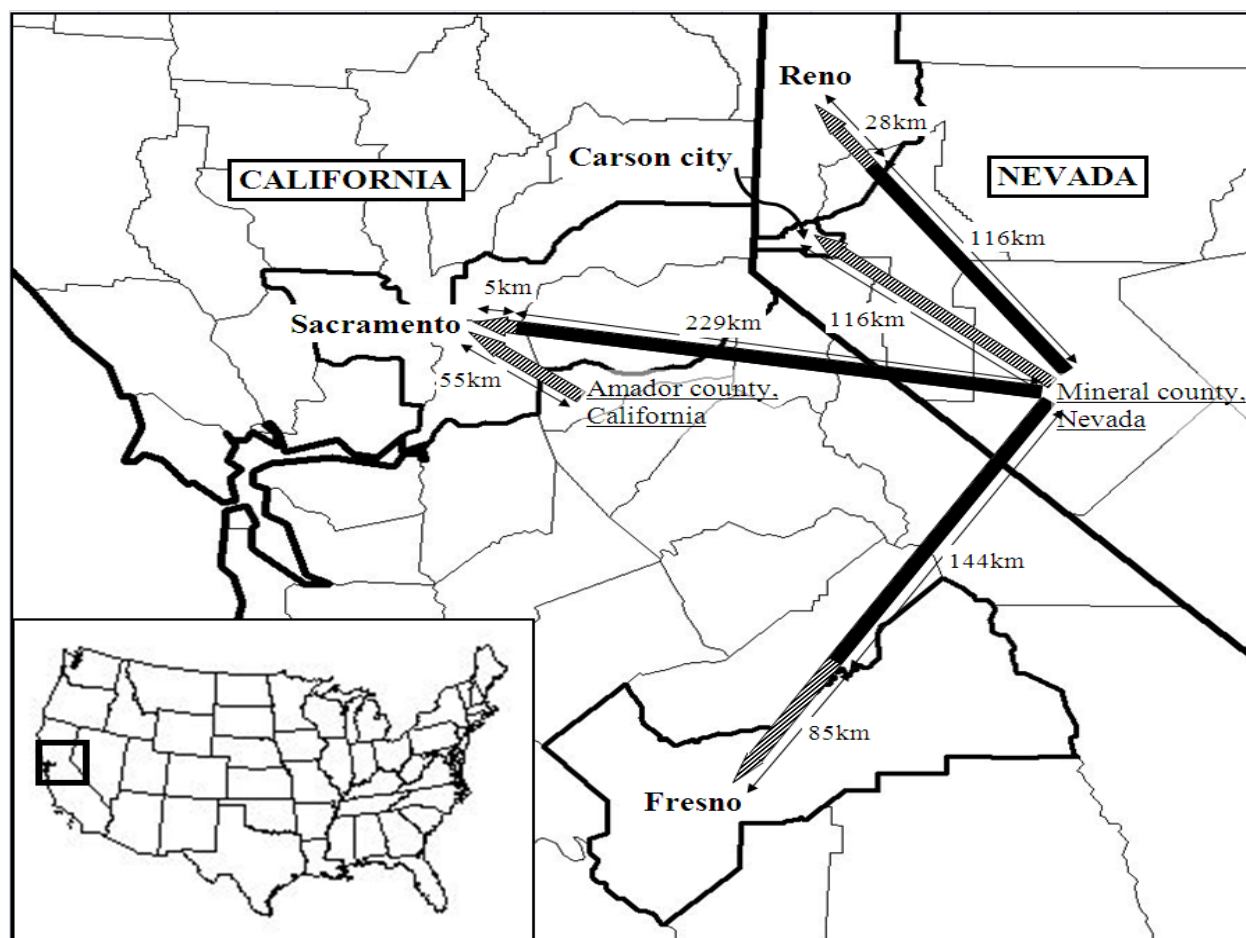
Our study uses data from the National Longitudinal Survey of Youth 1979, NLSY1979 (Center for Human Resource Research, 2009). The survey began in 1979 when its respondents were between ages 14 and 22. The survey was conducted annually until 1994 and biannually thereafter. In 2008, respondents were between the ages 44 and 52.<sup>10</sup> The NLSY79 includes detailed information on height, weight, demographic characteristics, income and assets, employment, and occupation over time. In the sample, 1.9% of respondents are underweight ( $15.99 < \text{BMI} < 18.5$ ).

<sup>7</sup> The within variation in BMI in the Eid et al. (2007) sample is 1.96, compared to 2.73 in our sample.

<sup>8</sup> See Section 5 for further discussion of the importance of this categorization.

<sup>9</sup> For the returner sample, we do not divide the sample between metropolitan and nonmetropolitan as there are not enough individuals returning and staying in nonmetropolitan areas for more than two years.

<sup>10</sup> The Hispanic sample represents Hispanic youths present in the United States in 1979 and was unchanged thereafter. Thus, Hispanics immigrating to the U.S. after 1979 are not represented in these data.

**Figure 2: Incremental Distances to the Urban Hierarchy**

The results are quantitatively and qualitatively similar with and without the underweight group. Our reported results exclude the underweight individuals.<sup>11</sup>

We augment the NLSY79 data with geocodes to identify individuals' county of residence. This information is then merged with the distance variables obtained from Partridge et al. (2007). These distance variables capture the distances of every county from different tiers of the urban hierarchy. As Figure 2 shows, Mineral County is 116 km from its nearest metropolitan area, while the incremental distances to reach a 0.25 million, 0.5 million, and 1.5 million people metropolitan area are 28 km, 85 km, and 5 km, respectively. In contrast, since the closest metropolitan area to Amador County has 1.5 million people (Sacramento), the other incremental distances are zero.

We believe that defining the location of individuals using these measures helps identify the obesogenic environment in a manner that is both unique and informative. It captures spatial access to a variety of amenities that influence individuals' body weight. Apart from time-varying demographic and economic characteristics such as age, education, marital status, family size, and income, we include two sets of variables that are relevant for explaining the variation in BMI. First, we include the variables "newborn" and "pregnant" to identify whether female individuals have a newborn or are pregnant. Second, we include two measures of job-related variables used in

<sup>11</sup> These results are available from the authors upon request.

Lakdawalla and Phillipson (2007): “physical demand,” which is a measure that rates the amount of climbing, kneeling, reaching, and stooping an individual does at his/her job, and “strength,” which measures the strength required to perform certain duties. We construct these variables using respondents’ standard occupational codes and matching them with the strenuousness and physical demand scales. County population density is calculated using land information from the decennial census and population information from the Bureau of Economic Analysis (BEA). Table 2 presents the summary statistics for all variables.

### 3. ECONOMETRIC SPECIFICATIONS

We estimate two sets of models to account for the unobserved characteristics and the possible endogeneity of location choice. The model described in Equation (1) is an individual fixed effects model<sup>12</sup> which accounts for unobservables but does not address the self-selection directly. The model in Equation (3) attempts to address the potential self-selection in location choice by focusing on a subset of movers who return to their county of origin. We use Equation (2) to conceptualize the source of endogeneity and how it could bias the estimates from Equation (1).

#### 3.1. Fixed Effect Estimation

The model to estimate the effect of various factors on BMI is

$$(1) \quad BMI_{it} = \beta_0 + \beta_1 D_{it} + \beta_2 X_{it} + \beta_3 Y_{it} + \eta_i + \varphi_i + \tau + \varepsilon_{it}$$

where  $BMI_{it}$  is the BMI of individual  $i$  at time  $t$ ,  $D_{it}$  is a vector of distances from different urban tiers,  $X_{it}$  is the vector of individual and family characteristics (age, education, marital status, health status, nature of physicality of the job, family size, family wage, etc.),  $Y_{it}$  is the vector of county characteristics (race composition of the population, measures of the urban sprawl of the county, i.e., density, distance to the nearest micropolitan/metropolitan area and incremental distance to the nearest meter),  $\eta_i$  is the individual-level unobserved characteristics,  $\varphi$  is the state fixed effect,  $\tau$  are the year dummies, and  $\varepsilon_{it}$  is the error term. The goal is to obtain a consistent and unbiased estimate of  $\beta_1$ .

The distance measures, however, may be endogenous. Suppose that  $D_{it}$  is the measure of  $R_{it}$ , the remoteness of the county of residence of individual  $i$  at time  $t$ . Let the model for  $R_{it}$  be

$$(2) \quad R_{it} = \alpha_0 + \alpha_1 X_{it} + \alpha_2 Y_{it} + \alpha_3 (Z_{it} * BMI_{it}) + \eta_i + \varphi_i + \tau + \epsilon_{it}$$

where  $Z_{it}$  is an individual-level indicator that indicates whether  $BMI$  matters in the determination of the remoteness of the county of residence and  $\epsilon_{it}$  is the error term. If the remoteness of the county the individual is moving to is influenced by the individual’s BMI, then  $Z_{it} \neq 0$ . Typically,  $Z_{it}$  is unobserved, and it is not feasible to evaluate  $Z_{it}$  for everyone. However, we may be able to identify a subset of individuals for whom  $Z_{it} = 0$ , in which case we can simply estimate Equation (1) to identify  $\beta_1$ .

We exploit the longitudinal nature of the data and estimate  $\beta_1$  using individual fixed effects. This eliminates the potential bias from  $\eta_i$ . Note that in these estimates, the assumption is that  $Z_{it} = 0$ .

<sup>12</sup> We bootstrap our standard errors and cluster them at the individual.



**Table 2: Summary Statistics**

	Full sample				Metro counties				Non-metro counties			
					male				male			
	(N = 62,839)				(N = 24,639)		female (N = 24,599)		(N = 7,147)		female (N = 6,454)	
	mean	sd	min	max	mean	sd	mean	sd	mean	sd	mean	sd
Body Mass Index (BMI)	26.24	5.54	7.60	85.93	26.54	4.65	25.73	6.24	26.82	4.90	26.39	6.28
<i>Position in the urban hierarchy</i>												
Incremental distance to nearest 0.25 million metro	23.44	59.94	0.00	584.49	21.13	60.59	21.08	60.52	32.98	59.31	30.64	54.01
Incremental distance to nearest 0.5 million metro	30.09	60.58	0.00	490.15	25.83	61.16	26.61	60.79	43.39	57.62	44.92	56.25
Incremental distance to nearest 1.5 million metro	84.35	128.76	0.00	599.21	79.69	128.32	84.10	131.36	92.56	123.03	94.04	125.60
<i>Density/sprawl measures</i>												
Density (hundreds per square mile)	9.54	16.63	0.00	121.81	11.90	18.20	11.97	17.94	0.84	0.65	0.89	0.67
Distance to nearest micropolitan/metropolitan area	14.28	19.92	0.00	221.55	12.76	13.98	12.51	13.74	20.72	32.83	19.66	33.26
Incremental distance to nearest metro	11.30	29.53	0.00	314.27	--	--	--	--	54.01	44.73	50.18	42.04
<i>Other covariates</i>												
% Black	0.29	0.46	0.00	1.00	0.31	0.46	0.31	0.46	0.24	0.43	0.23	0.42
% Hispanic	0.12	0.33	0.00	1.00	0.14	0.35	0.13	0.34	0.08	0.27	0.08	0.27
Age	32.93	7.42	20.00	51.00	32.68	7.32	32.93	7.48	33.40	7.45	33.40	7.48
Highest grade completed	13.12	2.32	0.00	20.00	13.11	2.42	13.40	2.25	12.46	2.20	12.79	2.07
Married	0.54	0.50	0.00	1.00	0.52	0.50	0.54	0.50	0.59	0.49	0.61	0.49
Family size	3.09	1.60	1.00	15.00	2.95	1.63	3.14	1.54	3.21	1.68	3.34	1.54
Real family wage (\$10,000, base year 1982)	4.90	4.35	0.00	68.14	5.17	4.49	5.04	4.54	4.28	3.73	4.03	3.48
Has a newborn	0.01	0.09	0.00	1.00	0.00	0.00	0.02	0.13	0.00	0.00	0.02	0.13
Pregnant	0.01	0.10	0.00	1.00	0.00	0.00	0.02	0.14	0.00	0.00	0.02	0.14
Measure of how physically demanding job is	1.81	0.85	0.00	3.93	1.96	0.92	1.57	0.69	2.22	0.92	1.73	0.67
Strenuousness of job	2.31	0.76	1.00	4.37	2.50	0.76	2.03	0.67	2.72	0.75	2.21	0.69

Notes: (a) All the distance measures are in kilometers. (b) The period covered is 1985–2008

### 3.2. Estimation with the Returner Sample

We cannot rule out the possibility that  $Z_{it} \neq 0$  for some individuals. In this case,  $\epsilon_{it}$  may be correlated with  $D_{it}$ . To break this correlation, we create a subsample, the *returner* sample (i.e., those who moved back to their childhood county). We assume that  $Z_{it} = 0$  for these individuals because the choice of location for the returners is more likely to be driven by family ties, familiarity with the area, and culture than the obesity-related characteristics of the area.

For this subsample of returners, we employ an event study approach and utilize the variation in remoteness before and after the move. This not only removes potential biases from  $\eta_i$  but also, under the assumption that  $Z_{it} = 0$  holds, breaks the potential correlation between  $\epsilon_{it}$  and  $D_{it}$ .

$$(3) \quad \Delta BMI_{it} = \gamma_0 + \gamma_1 \Delta D_{it} + \gamma_2 \Delta X_{it} + \gamma_3 \Delta Y_{it} + \xi_{it}$$

where  $\Delta$  indicates the difference in values between  $t + 1$  and  $t - 1$ , where individual  $i$  returns to his/her original county in survey year  $t$  and  $\xi_{it}$  is the error term.

While it is not possible for us to determine an individual's migration reason, there is considerable work showing that people who return to their county of origin are likely doing it for non-weight related motives. Mills and Hazarika (2001) find that the absence of matrilineal extended family in the area reduces the psychic costs of migration.<sup>13</sup> A return after an initial outmigration is determined primarily by the existence of these ties. Davanzo (1982) argues that a return migrant has substantial firsthand knowledge about the locations in which he/she lived before and that by returning, the migrant may be able to recoup some part of any location-specific capital he acquired there. Additionally, the magnitude of the share of these kinds of relocation is significant. Lansing and Barth (1967) report that barring job-related transfers (e.g., military transfers), nearly half of all moves are to locations in which the migrant has relatives, and seven out of ten moves are made toward locations in which, if the migrants do not have relatives, they at least have friends.

Table 3 compares the group of returners to the group of movers in our sample, the former being a subsample of the latter. The two groups do not differ in body weight. However, a returner is more likely to be Black, younger, and less educated with a lower income.<sup>14</sup> The group of returners also has a smaller proportion of married individuals and larger family size (indicating possible extended families). The event study approach, by construction, accounts for time-invariant unobserved heterogeneities (e.g., family background or upbringing). As for time-varying characteristics, we have included many time-varying observables to account for changes that took place within the window of the individual's life before and after the move.

Finally, for our results to have an upward bias, the childhood counties of the returners must be systematically more remote. In Table 4, we present the geographical characteristics of the childhood counties of the returners. We observe that, compared to a generic metropolitan area (nonmetropolitan) county, the childhood metropolitan (nonmetropolitan) counties are *not* systematically more remote. If anything, the childhood counties of the returners are substantially denser and less remote, especially for metropolitan counties.

<sup>13</sup> Within the push-pull framework, if relatives and friends are in the individual's community of residence, migration is deterred, but if they reside elsewhere, migration is more probable and directed toward their location (Lee, 1966).

<sup>14</sup> Davanzo (1982) finds that less educated individuals are more likely to return as a "corrective" action to their initial move.

**Table 3: Average Characteristics of Returners and All Movers**

Variable	All movers (mean)	Returners (mean)	<i>t</i> -statistic of difference of mean
# of individuals	3,244	1,217	
BMI	25.46	25.36	0.72
% Black	0.25	0.29	-3.24
% Hispanic	0.11	0.11	0.02
Age	31.39	30.46	4.54
Has a newborn	0.01	0.01	-0.53
Pregnant	0.01	0.01	0.33
HGC	13.45	13.05	5.38
Married	0.48	0.40	5.92
Family size	2.71	3.03	-6.71
Real family wage	45,106.45	38,005.51	5.67
Measure of how physically demanding job is	1.75	1.81	-2.56
Strenuousness of job	2.27	2.33	-2.43

## 4. RESULTS

### 4.1. Individual Fixed Effect Regressions

We present most of our results separated by gender to be consistent with the literature since obesity rates for women tend to be higher than those of men (Eid et al., 2008). Additionally, there are often differences between the obesity rates of men and women in a given location and there is evidence that men and women's physical activity levels are affected differently by the environment ((Duncan and Mummery, 2005; Van Cauwenberg et al., 2011). In Table 5, we pool metropolitan area and nonmetropolitan area counties and only include the distance variables and year dummies

**Table 4: Comparison between All Counties and the Childhood Counties of the Returners**

	Metro counties		
	All	Childhood counties of returners	<i>t</i> -stat difference of means
Incremental distance to nearest 0.25 million metro (km)	35.31	15.07	3.93
Incremental distance to nearest 0.5 million metro (km)	34.90	22.11	2.76
Incremental distance to nearest 1.5 million metro (km)	86.81	81.13	0.60
Density	353.21	879.09	-6.79
Incremental distance to nearest metro (km)	19.80	16.42	2.76
	Nonmetro counties		
	All	Childhood counties of returners	<i>t</i> -stat difference of means
Incremental distance to nearest 0.25 million metro (km)	51.87	32.11	1.99
Incremental distance to nearest 0.5 million metro (km)	41.88	31.25	1.36
Incremental distance to nearest 1.5 million metro (km)	86.12	78.59	0.56
Density	52.49	64.82	-1.96
Incremental distance to nearest metro (km)	30.78	31.72	-0.22
Distance to nearest micropolitan/metropolitan area	54.05	54.58	-0.09

**Table 5: Effect of Remoteness on BMI (Metro and Non-Metro Counties Combined)**

	ALL		Male		Female	
	(1)	(2)	(3)	(4)	(5)	(6)
Incremental distance to nearest 0.25 million metro (km)	0.0000	0.0006	0.0001	0.0006	-0.0001	0.0006
Incremental distance to nearest 0.5 million metro (km)	0.0011*	0.0017**	0.0014	0.0019**	0.0006	0.0014
Incremental distance to nearest 1.5 million metro (km)	-0.0005	-0.0005	-0.0008*	-0.0004	-0.0004	-0.0005
Density		-0.1272	-0.2700	-0.1614	-0.2266	-0.0735
Distance to the nearest micropolitan/metropolitan area	0.0005	-0.0002	0.0018	0.0017	-0.0013	-0.0015
Incremental distance to nearest metro (km)	0.0004	0.0005	0.0014	0.0018	-0.0012	-0.0011
Age		0.2381***		0.3049***		0.1906**
Age <sup>2</sup>		-0.0037***		-0.0041***		-0.0034***
Highest grade completed		0.0604		-0.0214		0.0817
Married		0.4517***		0.3257***		0.6353***
Family size		-0.0181		-0.0166		-0.0175
Real family wage		-146.4738***		14.9619		-294.7296***
Has a newborn		1.1761***				1.3156***
Pregnant		1.8180***				1.9800***
Measure of how physically demanding job is		0.0109		0.0322		-0.0100
Strenuousness of job		-0.0342		-0.0689**		-0.0600
Observations	62,839	62,839	31,786	31,786	31,053	31,053
R <sup>2</sup>	.357	.37	.387	.396	.345	.366
Year FE	5,994	5,994	2,964	2,964	3,030	3,030
Individual FE	yes	yes	yes	yes	yes	yes
State FE	no	yes	no	yes	no	yes
MSE	no	yes	no	yes	no	yes
Number of individuals	2.016	1.997	1.705	1.693	2.282	2.247

Notes: (a) Standard errors are bootstrapped and clustered at the individual level. (b) \*\*\*, \*\*, and \* indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

(column 1). The coefficients represent regression coefficients estimating the impact of each of the density and distance variables on BMI. Assuming  $Z_{it} = 0$ , we then estimate Equation (1) by adding density, individual- and family-level control variables, individual fixed effects, and state fixed effects column 2.<sup>15,16</sup> We add the state fixed effects to control for macroeconomic and other aggregate-level differences across counties. The specification also includes age-squared since it has been shown that there is a nonlinear relationship between age and weight (Eid et al., 2007). In the full specification, the only incremental distance to have a significant effect on an individual's BMI is distance to the nearest 0.5 million metro.

When we run the same specifications for men (columns 3 and 4) and women (columns 5 and 6) separately. Unsurprisingly, we find that being pregnant or having had a new baby in the

<sup>15</sup> Of course, the assumption that  $Z_{it} = 0$  may or may not hold for everyone. We therefore estimate Equation (3) and discuss these results later.

<sup>16</sup> As we state above, all regression standard errors are bootstrapped.

**Table 6: Regressions by Metro and Non-Metro Subsamples**

	Metro		Non-metro	
	Male	Female	Male	Female
Incremental distance to nearest 0.25 m metro (km)	0.0023***	0.00001	-0.0046	0.0050*
Incremental distance to nearest 0.5 m metro (km)	0.0034**	0.0013	0.0031	-0.0002
Incremental distance to nearest 1.5 m metro (km)	-0.0015***	-0.0007	0.0003	0.0009
Density	-0.1324	-0.2684	0.3448	-0.1366
Distance to nearest micropolitan/metropolitan area	0.0051*	-0.0053	0.0017	-0.0036
Incremental distance to nearest metro (km)			0.0003	-0.0039
Age	0.2988***	0.1681*	0.2863**	0.2016
Age <sup>2</sup>	-0.0039***	-0.0034***	-0.0046**	-0.0032
Highest grade completed	-0.0427	0.0415	-0.0505	0.0735
Married	0.3278***	0.6150***	0.3349***	0.7792***
Family size	-0.0156	-0.0151	-0.0541	-0.0166
Real family wage	-18.9424	-276.8279***	0.0134	-0.0299
Has a newborn		1.2553***		1.7376***
Pregnant		2.0809***		1.8141***
Measure of how physically demanding job is	0.0455	-0.0187	-0.0410	-0.0005
Strenuousness of job	-0.0782*	-0.0310	0.0194	-0.0803
Observations	24,639	24,599	7,147	6,454
R <sup>2</sup>	.407	.369	.355	.345
Number of individuals	2,581	2,638	908	846
Year FE	Yes	yes	Yes	yes
Individual FE	Yes	yes	Yes	yes
State FE	Yes	yes	Yes	yes
Individual clustering	Yes	yes	Yes	yes
MSE	1.644	2.205	1.678	2.156

Notes: (a) Standard errors are bootstrapped and clustered at the individual. (b) \*\*\* p<.01, \*\* p<.05, \* p<.1. (c). We were unable to calculate bootstrapped standard errors for the nonmetropolitan sample due to the small size.

past year are strong contributors to higher BMI for women. While the distance variables do not have any significant effect on BMI for women, incremental distance to the nearest metropolitan area with a population of 0.5 million remains significant for men, with a slightly larger coefficient compared to the full sample. One kilometer of incremental distance to the nearest 0.5 million metropolitan contributes 0.002 points to the BMI for men in metropolitan counties (i.e., a 0.32-point increase in BMI for 100 miles of incremental distance from the 0.5 million metro). The measures of sprawl/density do not influence BMI in the full specifications (columns 2, 4, and 6), which is in line with Eid et al. (2008).<sup>17</sup>

<sup>17</sup> A note on the magnitude of the distance effect: We are measuring the total cost of reaching the nearest highest-tiered city, which is affected by the costs to reach any potentially closer lower-tiered centers. With the developed U.S. road system, the distance terms should accurately proxy for travel time. For example, Combes and Lafourcade (2005) find that the correlation between distances and French transport costs is 0.97. As Partridge et al. (2008b) argue, if distances do not accurately reflect travel time, the measurement error would bias the distance coefficients toward zero, which works against finding distance effects, implying that the effects are likely stronger than what we report.

We divide the sample into metropolitan and nonmetropolitan counties using the 2003 metropolitan area boundaries from the U.S Census Bureau. As Table 6 shows, when we focus on our metropolitan sample, we find that for men in metropolitan counties, even after including time fixed effects, state fixed effects, individual fixed effects, a full set of covariates, and measures of sprawl/distance, the remoteness measures are significant: one kilometer of incremental distance from metros with a population of 0.25 and 0.50 million increases BMI by 0.0023 and 0.0034, respectively. Distance from a metropolitan of 1.5 million is inversely associated with BMI for men living in metropolitan counties (one kilometer of incremental distance reduces BMI by 0.0015 points). Some measures of urban sprawl are also significant in the metropolitan-male sample: both the distance from the nearest micropolitan/metropolitan and the incremental distance to the nearest metropolitan increase BMI. This is in contrast to the findings in Eid et al. (2008), perhaps because our sample covers a greater age range and has more variation. This could also be because of the potential endogeneity discussed earlier.

In the nonmetropolitan area regressions in Table 6, the only distance variable that is significant is distance from a metropolitan area with a population of 0.25 million for women: living in a nonmetropolitan area county 100 km away from a metropolitan of 0.25 million people contributes to a 0.5-point BMI increase for a woman. The sprawl/density measures are again not significant in the nonmetropolitan regressions in Table 6. The differences in effects between the metropolitan and nonmetropolitan area samples reinforce the idea that the benefits of agglomeration diminish with distance. In this context, the cost “weight penalty” associated with living far from a large city is not significant if the distance is prohibitive for regular trips for amenity purposes or responses to labor demand.

A curious case is the coefficient of the distance from a 1.5 million metropolitan for men in metropolitan counties, which is negative—that is, the BMI is lower with increased distance. While large urban areas provide amenities that help reduce weight, there are also disamenities such as pollution, traffic, and stress. The negative coefficient could mean that the benefits of proximity may be outweighed by the disamenities of living closer to the largest metros. The number of hours wasted in traffic, for instance, differs by the size of the urban area (Shrank and Lomax, 2010) which influences both the time available for exercise and the stress levels for urban and suburban residents: the yearly delay per auto commuter for small, medium, and large urban areas in 2010 was 18, 21, and 31 hours, respectively.<sup>18</sup> Block et al. (2009) find associations between psychological stress and weight gain.

## 4.2. Returners

As mentioned in Section IV, the assumption that  $Z_{it} \neq 0$  may or may not hold for all individuals. Then,  $\epsilon_{it}$  may be correlated with  $D_{it}$ . To break this correlation, we create the *homeward-bound* subsample (i.e., those who moved back to their childhood county). We identify 270 men and 214 women who returned to their county of origin for whom we have all the necessary information.

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<sup>18</sup> Small urban areas < 0.5 million people, medium urban areas < 1 million, large urban areas > 1 million.

**Table 7: First Difference Estimation for the Returner Sample**

	All counties	
	Male	female
$\Delta$ Incremental distance to nearest 0.25 million metro (km)	0.0070*** (0.001)	-0.0063 (0.006)
$\Delta$ Incremental distance to nearest 0.5 million metro (km)	-0.0008 (0.002)	-0.0024 (0.007)
$\Delta$ Incremental distance to nearest 1.5 million metro (km)	-0.0001 (0.001)	-0.0020 (0.002)
$\Delta$ Density	0.0028 (0.004)	0.0005 (0.005)
$\Delta$ Distance to the nearest micropolitan/metropolitan area	0.0133 (0.008)	0.0024 (0.008)
$\Delta$ Incremental distance to nearest metro (km)	0.0014 (0.002)	-0.0015 (0.003)
$\Delta$ Highest grade completed	0.3817 (0.316)	-0.1826 (0.279)
$\Delta$ Family size	0.0102 (0.050)	0.2090*** (0.058)
$\Delta$ Real family wage	0.0329 (0.042)	0.0308 (0.060)
$\Delta$ Measure of how physically demanding job is	0.0173 (0.160)	0.2998 (0.225)
$\Delta$ Strenuousness of job	0.0023 (0.229)	0.0755 (0.320)
Got married	-0.2471 (0.497)	0.3969 (0.469)
Stayed married	0.1413 (0.238)	0.5286 (0.458)
Was pregnant at (t-1)		-2.2607*** (0.351)
Was pregnant at (t+1)		0.4181 (1.000)
Had a newborn at (t-1)		-1.6530 (1.110)
Has a newborn at (t+1)		2.8588*** (0.877)
Observations	281	218
Number of individuals	270	214
$R^2$	.245	.332
Year FE	Yes	yes
State FE	Yes	yes
MSE	1.811	1.992

Notes: (a) The dependent variable is  $\Delta BMI_{it}$ , where  $\Delta$  indicates the difference in values between  $t + 1$  and  $t - 1$ , where individual  $i$  returns to his/her original county at time  $t$ . (b) Returners are those who moved back to the county where they grew up. (c) Numbers in parentheses report clustered standard errors, where clustering is done at the state level. (d) \*\*\*, \*\*, and \* indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively.

We run a first difference specification as given in Equation (3). The dependent variable is the difference in BMI between  $t + 1$  and  $t - 1$ , where the individual returns to his/her original

county in survey year  $t$ . The explanatory variables include the differences in all the continuous variables included in the regressions in Tables 4 and 5. As for dummy variables, we include changes in marriage status, pregnancy, and having a newborn. We also include the post-event year and state fixed effects. We also examine how length of stay affects the relationship between the distance variables of interest and weight. These length of stay regressions follow the same specification as our original first difference specified in Equation (3) but are restricted to different windows of stay (one year, two years, three years, and four years).

As Table 7 shows, our results in this preferred specification are weaker than the fixed effect estimation which does not account for self-selection. The only distance variable to impact weight is distance to the nearest metropolitan area with a population of 0.25 million contributes to a 0.007-point increase in BMI for men (i.e., a 1.13-point increase in BMI for 100 miles of incremental distance). The distance variables are not significant for women. In Table 8, we present the same regressions by the type of county that the individual returned to. For men who returned to a metropolitan county, incremental distance to the nearest 0.25 million metropolitan is again significant, with a slightly larger coefficient (0.008). The disamenities effect that we found for the largest metros in the fixed effects regression in Table 6 no longer remains. Distances are not

**Table 8: First Difference Estimation for the Returner Sample by County Type**

	Return to			
	Metro county		Non-metro county	
	male	female	Male	female
$\Delta$ Incremental distance to nearest 0.25 million metro (km)	0.0078*** (0.001)	-0.0079 (0.008)	0.0088 (0.020)	-0.0164 (0.056)
$\Delta$ Incremental distance to nearest 0.5 million metro (km)	-0.0027 (0.002)	-0.0024 (0.009)	0.0211 (0.014)	0.0201 (0.022)
$\Delta$ Incremental distance to nearest 1.5 million metro (km)	-0.0003 (0.001)	-0.0017 (0.003)	0.0037 (0.008)	-0.0038 (0.006)
$\Delta$ Density	0.0023 (0.005)	0.0039 (0.008)	0.0416 (0.036)	-0.0632 (0.066)
$\Delta$ Distance to the nearest micropolitan/metropolitan area	0.0104 (0.012)	0.0099 (0.013)	0.0122 (0.030)	-0.0255 (0.029)
$\Delta$ Incremental distance to nearest metro (km)	0.0045 (0.004)	0.0028 (0.016)	0.0002 (0.013)	-0.0181 (0.014)
Observations	224	173	57	45
$R^2$	.257	.337	.640	.840
Year FE	yes	yes	Yes	yes
State FE	yes	yes	Yes	yes
$\Delta$ Continuous variables	yes	yes	Yes	yes
Dummy variables	yes	yes	Yes	yes
MSE	1.894	2.085	1.704	1.853

Notes: (a) The dependent variable is  $\Delta BMI_{it}$ , where  $\Delta$  indicates the difference in values between  $t + 1$  and  $t - 1$ , where individual  $i$  returns to his/her original county at time  $t$ . (b) Returners are those who moved back to the county where they grew up. (c) Numbers in parentheses report clustered standard errors, where clustering is done at the state level. (d) \*\*\*, \*\*, and \* indicate significance at the 1 percent, 5 percent, and 10 percent levels, respectively. (e) The dummy variables and  $\Delta$  Continuous variables include the same variables as in Table 6.



**Table 9: First Difference Estimation of the Returner Sample Based on Length of Stay**

VARIABLES	$t-(t-1)$ One year	$t+1-(t-1)$ Two years	$t+2-(t-1)$ Three years	$t+3-(t-1)$ Four years
$\Delta$ Incremental distance to nearest 0.25 million metro (km)	0.0057*** (0.003)	0.0051 (0.006)	0.0047 (0.007)	0.0055 (0.013)
$\Delta$ Incremental distance to nearest 0.5 million metro (km)	0.0021 (0.002)	0.0030 (0.003)	0.0047 (0.003)	0.0023 (0.004)
$\Delta$ Incremental distance to nearest 1.5 million metro (km)	0.0025** (0.001)	0.0029** (0.001)	0.0019 (0.002)	0.0016 (0.002)
$\Delta$ Density	0.0082 (0.001)	0.0049 (0.004)	0.0062 (0.003)	0.0083 (0.004)
$\Delta$ Incremental distance to nearest metro (km)	0.0061 (0.005)	0.0095 (0.007)	0.0120* (0.0067)	0.0129 (0.008)
$\Delta$ Distance to the nearest metropolitan/metropolitan area	0.0076** (0.004)	0.0175*** (0.003)	0.0122*** (0.004)	5.85e-05 (0.010)
Observations	508	387	320	261
$R^2$	.237	.309	.309	.371
Year FE	yes	yes	Yes	yes
State FE	yes	yes	Yes	yes
$\Delta$ Continuous variables	yes	yes	Yes	yes
$\Delta$ Dummy variables	yes	yes	Yes	yes
S.E. clustered over state	yes	yes	Yes	yes
MSE	2.463	2.573	2.583	2.969

Robust standard errors in parentheses, \*\*\*  $p < .01$ , \*\*  $p < .05$ , \*  $p < .1$

metropolitan county, incremental distance to the nearest 0.25 million metropolitan is again significant, with a slightly larger coefficient (0.008). The disamenities effect that we found for the largest metros in the fixed effects regression in Table 6 no longer remains. Distances are not significant for women or for nonmetropolitan area counties. The sprawl/density measures are not significant in any of these regressions.<sup>19</sup>

Given that the consequences of the new location on weight may take some time to develop, we examine how returners' weight are affected by tenure length in Table 9. The results are inconsistent across groups but disappear for the group of returners who stay for four years indicating that the effects weaken over time. In general, our results show that, in the estimations not corrected for potential reverse causality, there is some evidence of greater distance from urban space leading to increasing BMI. These effects largely disappear once we account for self-selection.

<sup>19</sup> The first difference regressions reported in Tables 7 and 8 have the standard errors clustered over states. In the fixed effect regressions, we clustered the standard errors over individuals. In the returner sample, however, 469 of 484 individuals appear only once (i.e., a move to the original county took place only once). Thus, clustering over individuals is not very meaningful. We have also run these same regressions clustering the standard errors over counties. The results remain quantitatively and qualitatively unchanged.

## 5. CONCLUDING REMARKS

The existing research has primarily focused on the link between BMI and urban sprawl, but we find that such a causal link is tenuous. We study the effect of remoteness on BMI after accounting for urban density. We address econometric hurdles such as unobserved heterogeneity and self-selection and find that remoteness affects body weight in the fixed effects estimation. The results become weaker once we account for self-selection and, in fact, no significant relationship is found for returners four years post-move. These findings indicate that controlling for self-selection is important in better understanding the relationship between the environment and body weight.

While we show that the causal relationship between sprawl and BMI is tenuous for adults, it should be pointed out that Guettabi and Munasib (2014b) show that, after accounting for unobserved individual heterogeneity and resulting selection bias, BMI of children is, on the other hand, positively related to urban sprawl and negatively related to distance to large metros. This indicates that the mechanisms through which land use affects households may be more nuanced than currently understood.

The presumed interaction between physical space and BMI, however, is only part of the broader discussion regarding body weight, obesity and health. At a time when evidence of the costs associated with the obesity epidemic is overwhelming (Sturm, 2002), it incumbents upon the researcher to identify not only the underlying mechanisms of unhealthy weight gain but also quantify the relative effects of various obesogenic environmental factors. This will help us devise policies that are more likely to work while avoiding misallocation of resources towards policies that are not likely to have meaningful impacts.

In spatial and regional economics, location choice related sorting is a common and recurring source of complication in econometric identification. We believe that, methodologically, our strategy of utilizing the ‘returner’ sample is an effective tool in this regard, and that it may be utilized in addressing other researcher questions that face a similar econometric hurdle.

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