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Climate Preferences, Obesity, and Unobserved Heterogeneity in Cities*

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Abstract: Some sources of heterogeneity among cities, i.e. age, gender, race, income, and education, have been the object of substantial inquiry. The reasons are obvious. These differences are easily observed and may have important implications for economic activity. This study considers another potentially important population characteristic, obesity. Descriptive statistics reveal that the intercity variance in obesity rates is substantial. Empirical results demonstrate that demographic and regional amenity variables all help to explain intercity differences in obesity. Because obesity is important for climate preferences, health, and productivity, its omission from previous studies and its correlation with amenity and demographic characteristics could create problems for empirical research.

Keywords: location, obesity, climate preferences, unobserved heterogeneity in cities
JEL Codes: I12, J10, R23

1. INTRODUCTION

It is well known that obesity is negatively associated with income and education.[1] Age, ethnicity, race, and gender effects are more complex but certainly significant.[2] Because cities differ in composition along income, education, age, race, ethnicity, and gender dimensions, they should naturally differ in obesity rates. However, a simple comparison of obesity rates across cities suggests that other factors may be influential. Approximately 42.7 percent of the population of the San Francisco-Oakland, CA MSA has a non-obese Body Mass Index (BMI < 25) while 20.7 percent are obese (BMI > 30). In contrast, in the Detroit, MI MSA percentages are 29.2 percent non-obese and 35.6 percent obese. Could such differences in obesity rates be due to observable age, race, ethnicity, gender, education, and income characteristics of

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[1] Much of this knowledge is based on the questions in the National Longitudinal Survey of Youth. This sample is inadequate to test the hypotheses regarding intercity differences being examined here. It is quite adequate to demonstrate differences in BMI associated with personal characteristics. The other source of BMI data is the National Health Inventory Survey, which is annual, but only identifies 33 MSAs. This number is too small for the analysis of the effects of differences in city characteristics undertaken here.

[2] Both Cawley (2015) and Courtemanche et. al. (2015) provide an excellent review of the economics of obesity literature

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individuals in the population of these cities or are specific city characteristics differentially attractive to the obese?

The question addressed in this paper is whether, in addition to observable personal characteristics of their inhabitants, city amenities, particularly climate, are associated with differences in obesity.[3] The literature reviewed here suggests several reasons to believe that differences in climate, topography, and, of course, food prices, make cities differentially attractive to individuals with a high BMI. This differential attraction may then cause individuals to select into these cities through migration. To the extent that differences in BMI are hereditary and city amenities are permanent, past migration may also select those prone to obesity into certain cities. BMI differences among cities may be the result of current or past migration of individuals with characteristics that influence BMI.[4] Alternatively, there may be a "BMI adaptation effect" as individual BMI adjusts in response to city characteristics. Regardless of the process, both migration and adaptation effects may contribute significantly to the large spatial differences in BMI documented in this paper.[5]

Why is the possibility that spatial characteristics play a role in determining BMI differences in the resident population important? First, general interest in obesity is high because of its strong connection with the development of type 2 diabetes mellitus (DM) and other ailments that impose substantial costs on society. Recent estimates of these costs are as large as 1.1 trillion dollars per year for the U.S. economy.[6] Second, there is an important issue for empirical research in economics. BMI is generally unobservable to the econometrician. Nevertheless, BMI is an important determinant of worker productivity partly due to direct effects and indirectly through the connection between obesity and DM. Therefore, BMI is correlated with variables such as income, education, and demographic characteristics that are important in empirical research. This raises the possibility for omitted variable bias in estimates of the effects of these personal characteristics on measures of wage differentials for constant quality workers and in a variety of other empirical research. Alternatively, if BMI is related to city amenity characteristics, this unobserved association could confound inferences about causes of spatial wage or productivity differentials across cities.[7] Could it be that a significant portion of the wage differential between observationally similar workers in San Francisco and Detroit is due to unobserved differences in their BMIs?[8]

Finally, recent advances by Bayer and Timmins (2007) and Bayer et al. (2009) have allowed estimation of the marginal willingness to pay for specific amenities by individual

[3] Philipson and Posner (1999) is perhaps the first paper in the economics of obesity literature to consider the effect of local environment on obesity status. However, they are interested in explaining cross-country variation in obesity, whereas here the focus is on a within-country, cross-city variation.

[4] The BMI selection effect has created problems in the literature on the effects of "sprawl" on BMI. There is substantial disagreement in this literature. See, for example, Eid et. al. (2008) versus Zhao and Kaestner (2010). This paper does not claim that differences in city amenities cause differences in BMI or that these differences selectively attract migrants with different BMIs. Either mechanism is consistent with the theory developed here. This paper is not about the causes of BMI variation among individuals but about the spatial variation itself.

[5] It may be that individual expectations for "optimal" BMI are based on community standards and that behavioral economics could explain local variation in diet and exercise. Following Anomaly and Brennan's (2014) recent suggestion, the analysis can be viewed as testing a rational choice model.

[6] Brookings Institution Study. See: http://www.brookings.edu/blogs/brookings-now/posts/2015/05/societal-costs-of-obesity

[7] There is a substantial quality of life literature following Roback (1982) that relates wage differentials to city amenities under the assumption that amenities have no effect on obesity or other unobservable population characteristics.

[8] Observational equivalence in this case refers to research that does not observe worker body mass index (BMI).

households. This research has revealed significant diversity in the marginal willingness to pay for environmental amenities, even after controlling for age, education, and income. Recently, Sinha and Cropper (2015) have found substantial heterogeneity in responses to city climate. Specifically, they find households sort spatially based on climate preferences and that preferences for higher winter temperatures are negatively correlated, $\rho = -0.83$, with preferences for higher summer temperatures. This spatial sorting and distribution of preferences has a substantial effect on the computation of total willingness to pay to avoid such climates. Could the spatial sorting that produces these strange climate preference effects be due to spatial sorting based on BMI?

Recent availability of large scale individual survey data on BMI for a representative sample of city populations allows testing of the hypothesis that, holding income, education, and demographic characteristics constant, selected city characteristics have a significant relation to their obesity rates.[9] The object of this study is to test the hypothesis that the city characteristics that are expected, based on physiological effects of obesity, to make areas differentially attractive to those with high BMI, have an influence on the average BMI and obesity rate in the city.

The next section of this paper develops the theoretical rational for believing that there is a BMI selection effect in which city characteristics have a differential attraction for obese individuals. Then, the available literature that relates BMI to preferences for climate, topography, and other city characteristics is reviewed. The data section discusses the construction of variables designed to measure these city differences. Finally, empirical results show general agreement between prior expectations and the obesity rate of cities.

2. THEORY: BMI AND CHOICE OF LOCATION

Assume that there are multiple households differentiated by a single scalar characteristic, b, which is an "inherited" property of individuals.[10] They must choose a location among areas indexed by j that are differentiated by wages, $\boldsymbol{w_j}$, transportable goods, x, whose price everywhere is p, non-transportable goods, h, for "housing" whose price, $\boldsymbol{r_j}$, varies spatially, and local amenity whose implicit price, $\boldsymbol{q_j}$, varies spatially. The indirect utility of a particular household, i, in location j can be written as:

$$(1) \qquad \boldsymbol{u_{ij}} = v(\boldsymbol{w_j}, p, \boldsymbol{r_j}, \boldsymbol{q_j}; \boldsymbol{b_i})$$

Taking the total differential of indirect utility under the assumption of constant utility across cities and solving for $\boldsymbol{dw_j}$, gives:

$$(2) \qquad d\boldsymbol{w_j} = -\lambda_{xw}dp - \lambda_{hw}d\boldsymbol{r_j} - \lambda_{qw}d\boldsymbol{q_j}$$

where λ_{yz} is the ratio of the partial derivative $V(.)$ with respect to y divided by the partial of $V(.)$ with respect to z.[11]Applying Roy's identity, the relation in equation (2) can be solved for the total derivative of earnings:

[9]The Center for Disease Control Behavioral Risk Factor Surveillance System surveys of individual BMI used in this study have been conducted for many years but, over the past 15 years the sample size increased significantly so that reliable estimates of BMI differences across a range of cities are possible.

[10] For purposes of this model, it does not matter whether b has a genetic origin or if it is learned in childhood.

[11] Note that (1) can be written in implicit form and provide a clear statement of the spatial iso-utility condition.

(3) $$d\boldsymbol{w_j} = \boldsymbol{x_j}dp + \boldsymbol{h_j}d\boldsymbol{r_j} - \boldsymbol{a_j}d\boldsymbol{q_j}$$

which, assuming $dp = 0$, implies that:

(4) $$d\boldsymbol{w_j} = \boldsymbol{h_j}d\boldsymbol{r_j} - \boldsymbol{a_j}d\boldsymbol{q_j}$$

Equation (4) states that the equilibrium tradeoff between wages and rents depends on the quantity of amenity consumed by the individual. It follows from the effect of *b* on indirect utility of the amenity that $da_j/db > 0$ and high *b* households will require a smaller compensating differential in wages than low *b* households to live in areas where the price of the amenity in question is lower.

Obviously, the *b* factor relevant for this research is BMI and the hypothesis is that the relative concentration of high BMI individuals will rise in areas where the prices of climate and other amenity factors that are differentially attractive to the obese are low (which implies the quantities of such amenity factors are high). This is not to say that the obese prefer harsher climates. It is simply sufficient that they have relatively lower willingness to pay for pleasant climates compared to the non-obese. This spatial sorting of population by BMI could arise through migration and/or adaption to environmental conditions. Ford (2005) has noted that migration is one possible sorting mechanism under the hypothesis that the tendency to be obese varies significantly in the population. Alternatively, Piziak (2010) and Andersson (2011) contend that heredity is an important determinant of BMI. This suggests that spatial differences in BMI could be the result of prior migration by those with a genetic predisposition to obesity. Finally, Chen (2013) has observed that standards of diet and exercise could vary spatially based on the interaction of preferences, which vary with BMI, and the relative proportion of the obese in the population. Thus, individuals may vary their BMI based on the social and environmental characteristics of their location. Put simply, even if migrants are homogenous, their behavior at the destination may be an adaptation to the conditions that they find there.

This paper does not test the exact mechanism that accomplishes the sorting. However, results indicate that the effects of climate and topography on BMI for individuals under 25 years of age are identical to those effects for individuals 25 or older, which is consistent with either effects of past migration or adaptation to local conditions. To the extent that migration occurs at ages greater than 24, this suggests that differences in BMI are not due to recent migration but rather to differences in the resident populations of areas that could be the result of past migration or early adaptation of youth to local conditions.[12]

3. EFFECTS OF INDIVIDUAL AND CITY AMENITY CHARACTERISTICS ON OBESITY

BMI itself is a measure solely based on the height and weight of the individual, but the literature identifies other individual characteristics that may explain variation in BMI such as income, education, gender, age, and race.[13] The empirical evidence strongly suggests that obesity varies inversely with both income and education (Baum 2004). The underlying reasons for this relation are not clear and may be quite complex but the relation holds within and across cities.

[12] Limited sample size and the discrete categories of age did not permit testing of BMI effects for younger age cohorts.

[13] We use a correction for BMI from Jain (2010) that adjusts the self-reported height and weight for age, gender, race / ethnicity.

Females have lower BMIs.[14] Age effects are non-linear because there is a tendency for BMI to be highest in middle age (Gallup 2012). To the extent that income, education, gender, and age are distributed unequally across cities, they may explain a significant portion of the variation in spatial obesity rates. In addition, race and ethnicity are also unequally distributed across cities and may have an independent relation to BMI. The purpose of this research is not to sort out the causal relation between these factors and BMI but rather to test whether spatial differences in their distribution can explain the large differences in BMI and obesity across cities or if other factors involving population selection based on amenities are important.

Much of the literature on amenity factors, whose attractiveness might vary with individual BMI, lies outside of economics because physiology is the basis for differences in preferences. Simply put, endomorphs react differently than ectomorphs to the same environmental conditions.[15] Examination of the literature reveals several area characteristics that should relate to obesity because the preferences of the obese are observed to differ from the average and thin populations. These preferences are the result of physiological effects of obesity. A substantial literature, stemming from seminal work by Roback (1982,1988), classifies these factors as local amenities. First of these are opportunities for outdoor recreation. City characteristics including access to water and parkland should be valued less by the obese. Secondly, the obese have difficulty dealing with certain topographic characteristics. Voss (2013) has found that elevation and elevation change are more physically demanding for the obese. Accordingly, individuals with high BMI will avoid mountainous locations and seek relatively flat coastal locations because of both topography and oxygen availability. Sunshine and BMI are negatively correlated according to Geldenhuys et. al. (2014). BMI may have significant effects on preferences for climate. Lin (2007) argues that given that exercise is associated with lower BMI, individuals with high preference for fitness and exercise will be relatively more attracted to places with mild summers and mild winters. Cold winters are more uncomfortable for those with lower BMI and hot summers make outdoor recreation more difficult. At the same time, cold winters and hot summers may make outdoor exercising difficult and the lack of exercise may lead to higher BMI. However, Dehghan et. al. (2013) found obese workers suffered more cardiac strain than their non-obese colleagues in hot and humid conditions, suggesting that the obese may be willing to pay to avoid such climates. Whether mild summers are associated with higher or lower BMI depends on whose willingness to pay dominates. We take no position on these findings in the previous literature except to include these variables identified by the public health, nutritional, and exercise researchers. One limitation of the explicit measures of environmental amenity discussed above is that measures of parkland, bodies of water, etc., are not adjusted for quality of the recreational experience that they provide. To the extent that the quality dimension of these local amenity variables is missing, there is measurement error that causes attenuation bias in estimates of the amenity effect.

Research on obesity has isolated a number of other non-amenity factors that tend to repel the obese and/or attract ectomorphs. Edwards (2008) identified the availability or use of public mass transit, Booth (2005) cited housing density, and both Dragone (2012) and Grossman (2013)

[14] CDC/NCHS, Health, United States, 2014, Table 64. Data from the National Health and Nutrition Examination Survey (NHANES)

[15] Ectomorph body types are thin and linear, while endomorph body types are round and composed proportionally with more fatty tissue. Mesomorph body types are more muscular than either ectomorphs or endomorphs. For a detailed description of these body types (as well as a history of how these terms developed), see Vertinsky (2007).

pointed to the cost of food as factors that may relate to obesity rates in an area. These additional factors are added to the empirical analysis.

4. DATA ON BMI AND URBAN AMENITY FACTORS

In relating cross-sectional variation in body mass index (BMI) to the city characteristics identified above, availability of data has previously been a major constraint. The source of BMI data for this study is the 2010 Center for Disease Control (CDC) Behavioral Risk Factor Surveillance System (BRFSS) survey of BMI at the individual and 2010 CDC SMART data (derived from the 2010 CDC BRFSS) at the MSA level.[16] The BRFSS was originally intended for use in state-level studies of obesity but recent expansion of the sample size accommodates use in MSA-level studies. The CDC survey includes calculated BMI and self-reported income, education, age, and various other demographic variables.

The CDC survey overcomes the greatest challenge to research on the spatial distribution of BMI. This is a telephone survey covering all 50 states and including over 400,000 individuals. The data includes a calculated BMI for each respondent (*bmi*) that is based on responses regarding height, weight, age, and gender. The CDC relates BMI to healthy weight status. Individuals with $bmi \geq 30$ are considered "obese", $25 \leq bmi < 30$is classified as "overweight", and individuals with $18 \leq bmi < 25$ are "normal" or "healthy weight". Finally, "underweight" individuals have $bmi < 18$. Thus, the BMI measure may also be used to classify individuals as obese or non-obese. However, one difficulty with the BMI computation is that it does not consider muscle mass. In addition to the endomorphs, there are mesomorphs who have rather high BMI. Given that mesomorphs may be at least as physically fit as ectomorphs, they likely have similar preferences. Accordingly, the inability to adjust BMI for muscle mass likely works against finding differences in the spatial distribution of BMI based on amenity factors.

Another issue with using BMI from the BRFSS is that both height and weight are self-reported. Numerous studies find that self-reported weight is measured with error.[17] To address this issue, we employ a correction to self-reported height and weight developed in Jain (2010) specifically for recent waves of the BRFSS.[18] Jain's adjustment formula is a function of age, race/ethnicity, and self-reported height and weight. We do not expect meaningful differences in estimation results using corrected or uncorrected measures of BMI, as Courtemanche (2011) notes that, "Researchers have generally found that the correlation between actual and self-reported BMI is very high, and that correcting for measurement error does not substantially alter the coefficient estimates in regressions."

Based on the 2010 CDC SMART data summaries by MSA, Honolulu, HI has the highest positive difference between the percent of individuals who are normal weight (43.9 percent) and the percent who are obese (43.9 – 21.2 = 22.7 percent). On the other end of the spectrum, McAllen, TX has the most substantial negative difference between the percent of individuals who are normal weight (22.7 percent) and the percent who are obese (22.7 – 41.7= –18.9

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[16] In its technical documentation, the CDC defines geographies using MMSAs (http://www.cdc.gov/brfss/smart/smart_data.htm). However, MMSAs and CBSAs are equivalent (http://www.census.gov/population/metro/) and this study focuses on metropolitan areas (MSAs). MSAs are defined using a state county to MSA crosswalk published by the US Census (http://www.census.gov/population/metro/files/lists/2009/List1.txt). Using the most recent crosswalk file from 2013 produced similar results (http://www.census.gov/population/metro/data/def.html).

[17]Cawley (2004), Burkhauser et al. (2009), O'Neill and Sweetman (2013), Courtemanche (2014), Dutton and McClaren (2014)

[18] Estimation results did not materially change whether using corrected BMI measures or unaltered self-reports.

percent). This illustrates the potential for spatial variation in BMI to have a substantial influence on differences in preferences and productivity of the population of cities.

Recalling the example noted at the start of this paper, the San Francisco – Oakland, CA MSA includes 42.7 percent with normal weight BMI and 20.7 percent who are obese for a BMI difference of 22 percent. Its average January temperature is 50 degrees while the average July temperature is 58 degrees. In contrast, the Detroit, MI MSA population ratios are 29.2 percent normal and 35.6 percent obese for a BMI difference of −6.4 percent. Detroit's average January and July temperatures are 25 and 74 degrees, respectively. Recalling that cold winters may repel ectomorphs due to their greater physiological response and hot summers make outdoor recreation more difficult, the difference between the BMI ratios of San Francisco (mild winter and mild summer) and Detroit (cold winter and warm summer) appears to be consistent with expected climatic effects. Thus, differences in climate that are pure amenity effects may have dramatic implications for unobserved heterogeneity, BMI in this case, of city population.

The BRFSS reports individual level information on household income, education, gender, and age. Respondents self-report age as a continuous measure but report household income and education by selecting the appropriate range or value from a categorical list. The statistical analysis uses these categories. Therefore, this paper models BMI as a step function of income and education along with continuous variables for age and indicator variables for race/ethnicity and gender.

Table 1 provides descriptive statistics for income, education, age, race, ethnicity, gender, intra-MSA location (e.g. central county, suburban county), and BMI from the BRFSS individual micro data. As indicated in Table 1, 191,215 persons reside in one of the 110 MSAs included in this study, and of these individuals, 1 percent of individuals surveyed are under-weight, 29 percent are normal-weight, 36 percent are overweight, and 34 percent are obese.[19]

Table 2 details descriptive statistics for the city characteristics (amenity and non-amenity) that are potentially related to BMI for individuals in the 110 MSAs where temperature data is available. Non-amenity factors include 2010 U.S. Census estimates of the total population (*Pop(100k))* expressed in hundreds of thousands, percent of the population that regularly uses mass transit, (*Transit%)*, and the density of housing, (*Density)*. Data from the American Chamber of Commerce Research Association (ACCRA) food cost index, (*gCOLA)*, measures the cost of groceries.

Three topographic factors commonly used to reflect local amenity that relate to BMI, are considered. The percentage of total MSA area covered by water, (*Waterarea)*, is taken from the 2010 U.S. Census. A second topographic variable, (*Coastal)*, is a binary indicator variable for MSA coastal location, (Atlantic, Pacific, Gulf of Mexico or Great Lakes) using National Oceanic and Atmospheric Administration (NOAA) coastal county definitions.[20] Coastal locations give more opportunity for outdoor activity but they are also generally flatter and near sea level. Recreation activity attracts those with lower BMI but flat terrain and low altitude make mobility easier for the obese. The percent of the MSA composed of park and recreation space, (*Parkland%)*, is available from the 2010 American Fitness Index, but only for a subset of

[19] These summary calculations employ the correction noted by Jain (2010)

[20] This variable equals 1 if the MSA's primary city is located in a NOAA identified Coastal County.

cities.[21] Clearly, this local public good should be valued less by the obese. Elevation in thousands of feet above sea level, (*Elevation)*, may influence obesity for two reasons. First, it is associated with

Table 1: Descriptive Statistics Individual Characteristics

Variable Name	Observations	Average	Standard Deviation	Minimum	Maximum
Body Mass Index					
BMI	191,215	28.55	6.19	6.80	93.69
BMI Category					
Under weight	1,590	0.01	0.09	0.00	1.00
Normal weight	55,703	0.29	0.45	0.00	1.00
Over weight	69,150	0.36	0.48	0.00	1.00
Obese weight	64,772	0.34	0.47	0.00	1.00
Age	191,215	55.85	16.79	7.00	98.00
Age^2	191,215	3,401.78	1,858.70	49.00	9,604.00
Age < 25	6,632	0.03	0.18	0.00	1.00
Female	116,288	0.61	0.49	0.00	1.00
Male	74,927	0.39	0.49	0.00	1.00
White, Non-Hispanic	144,255	0.75	0.43	0.00	1.00
Black, Non-Hispanic	19,788	0.10	0.30	0.00	1.00
Hispanic	13,755	0.07	0.26	0.00	1.00
Other	13,417	0.07	0.26	0.00	1.00
Elem or less	4,685	0.02	0.15	0.00	1.00
SomeHS	9,829	0.05	0.22	0.00	1.00
HS	49,045	0.26	0.44	0.00	1.00
SomeCL	49,860	0.26	0.44	0.00	1.00
BA	77,486	0.41	0.49	0.00	1.00
Income <15K	16,459	0.09	0.28	0.00	1.00
Income >=15K&<20K	11,446	0.06	0.24	0.00	1.00
Income >=20K&<25K	14,610	0.08	0.27	0.00	1.00
Income >=25K&<35K	18,141	0.09	0.29	0.00	1.00
Income >=35K&<50K	23,862	0.12	0.33	0.00	1.00
Income >=50K&<75K	26,495	0.14	0.35	0.00	1.00
Income >75K	56,194	0.29	0.46	0.00	1.00

Notes: Un-weighted Survey Responses

[21] Parkland data for 49 MSAs comes from the 2010 American Fitness Index (AFI).The AFI adjusts Trust for Public Land (TPL) data to exclude parkland such as wildlife refuges (considered outside the built area of a city) such as those found in New Orleans. To supplement this data, we also use 2010 TPL data that allows us to add parkland data for 13 more MSAs. For these cities, only El Paso appears to have significant wildlife parkland that the AFI may have removed had El Paso been one of the 50 largest MSAs. Importantly, the estimation results are not sensitive whether this adjustment is to El Paso's data or not.

Table 2: Descriptive Statistics City Characteristics

	Observations	Average	Standard Deviation	Min	Max	25th Percentile	75th Percentile
Average BMI	110	28.77	0.061	27.09	30.13	28.45	29.13
Urban Characteristics (Y variables)							
gCOLA	110	100.93	11.07	79.80	160.10	92.7	105.9
Transit%	110	0.03	0.04	0.00	0.31	0.01	0.03
Density	110	197.90	196.19	9.00	1125.70	66.9	259.7
Pop (100k)	110	17.70	25.82	0.92	189.20	4.15	20.76
Topography (Z Variables)							
Waterarea%	110	0.09	0.14	0.00	0.72	0.009	0.08
Coastal	110	0.35	0.48	0.00	1.00	N/A	N/A
Elevation	110	1.04	1.40	0.00	6.18	0.132	1.064
Parkland%	62	10.14	6.03	1.58	28.14	5.3	14.2
Climate (Z variables)							
Jan	110	38.07	12.14	9.30	73.20	29.2	46.3
July	110	77.55	6.05	57.70	94.20	73.5	82.1
JanSun	78	52.15	12.07	28.00	80.00	45	58
JulySun	78	70.27	8.11	57.00	97.00	64	74
Precip	110	35.77	15.05	4.19	66.15	22.2	46.63

uneven terrain and second with lower oxygen content. City elevation is based on the elevation of the local weather station whose selection is discussed below. We include city elevation as these are hypotheses from the literature (such as Voss 2013).

Climate characteristics are potentially very important in determining differential amenity preferences for the obese. The climate variables are measured using observations from NOAA weather stations; with preference given to major city airports as these typically report all climatic data of importance.[22] The climate variables listed in Table 2 include the average recorded temperature in January (*January*) and July (*July)*, annual precipitation (*Precip)*, and average sunshine for the months of January and July *(JanSun* and *JulySun)*. Using averages over the 1981-2010 period smooths idiosyncratic variation in temperature and sunshine assuming that individuals locate based on expectations of past climate. Individuals with low BMI should have a more negative physiological response to cold winters and prefer summer climate that is not very hot or rainy so that outdoor activity, particularly exercise, is pleasant.

5. STOCHASTIC SPEFICATION

The study employs a cross-sectional design to test the relative effects of otherwise time-invariant amenities and city characteristics. This is not possible in a pooled cross-section or panel

[22] Of course, for some cities, the major airport is located in the center of the city (Washington, DC or San Diego, CA) or for others it is located several miles further out in the suburbs (San Francisco, CA or Chicago, IL).

study design with time and area fixed effects because city characteristics and amenities are largely time-invariant over say, a decade. The hypothesis tested here is that the variation in BMI across cities is due to both variation in individual characteristics and amenities among cities. Specific hypotheses regarding the effects of individual amenities were developed because of specific differences in the effects of BMI on preferences, including physiological responses to amenities. The resulting BMI equation can be written as:

$$\boldsymbol{b_i} = \alpha + \Sigma_h \lambda_h \boldsymbol{X_{hi}} + \Sigma_j \beta_j \boldsymbol{Y_{ji}} + \Sigma_k \theta_k \boldsymbol{Z_{ki}} + \varepsilon_i \quad (5)$$

where: b_i is the BMI of individual i, $\boldsymbol{X_{hi}}$ is a matrix of observations of income, education, race, ethnicity, gender and age variables, $\boldsymbol{Y_{ji}}$ is a matrix of observations of j area characteristics that might influence BMI, $\boldsymbol{Z_{ki}}$ is a matrix of climate and topographic amenity variables for which preferences may depend on BMI as discussed in the theory section. α, λ, β, and θ are parameters to be estimated, and ε is a residual error term. Lastly, measurement errors in the BRFSS survey may be correlated at the MSA level due to sampling factors. Accordingly, standard errors are clustered at the MSA level. The estimations use respondent survey weights from the BRFSS data file.

There are strong prior expectations for the signs of most of the estimated parameters. Table 3 provides estimation results for BMI (*bmi)* across different MSA samples based on the differential availability of sunshine and parkland data. Model 1 displays individual level estimation results across the 110 MSAs with temperature and amenity data. Model 2 adds parkland data to the specification in Model 1, and accordingly restricts the analysis to the smaller sample of MSAs where this data is available. Model 3 contains estimation results for individuals across 78 MSAs with temperature, sunshine, and amenity data. Model 4 adds in AFI/TPL parkland data to the specification from Model 3.

Estimation across Models 1-4 in Table 3 yields exceptionally consistent results. BMI first rises and then falls with age. Women have slightly lower BMI than men.[23] Race and ethnicity have a substantial relation to BMI. Individuals with more education and household income have lower BMI. These are all personal characteristics of the resident population that, based on non-spatial analysis of the determinants of BMI, were expected to be important. Among the non-amenity variables, higher food costs, as expected, are associated with lower BMI.

The expected relation between climate or topography amenity variables and BMI that was based on physiological factors tends to hold in the Table 3 results. Cities with milder January temperatures (*Jan)* and/or increased sunshine (*JanSun*) have lower individual BMI, while cities with hotter July temperatures (*July*) that discourage exercise have higher BMI. Of the topographic variables, elevation (*Elevation*) and Coastal location (*Coastal*) are statistically significant, and, as expected, both have a negative relation to BMI.[24]

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[23] In the 2010 BRFSS individual level dataset among the 110 MSAs studied, the average male BMI is 28.6. For women, average BMI is 27.9. Therefore, the statistically significant and negative effect of gender on BMI is consistent with the underlying data.

[24] An astute referee suggested that elevation may not be an ideal measure for topographical flatness. The point is valid, as San Francisco has low elevation but is quite hilly. Further, we expect hilliness to have a negative relation to BMI. We re-estimated our models including an ordered rank measure of hilliness of U.S. cities from Kolden and Pierce (2015). When hilliness is included, the estimated effect of Coastal remains negative but is not statistically significant, but we find no other material difference in sign, significance, or magnitude of coefficient estimates presented here (the estimated effect of hilliness on BMI is negative, consistent with our expectations).

Table 3: Empirical Results (Dependent Variable – Individual BMI)

	1	2	3	4
Age	0.2971***	0.2968***	0.2937***	0.2945***
	(0.000)	(0.000)	(0.000)	(0.000)
Age^2	-0.0025***	-0.0025***	-0.0025***	-0.0025***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.8710***	-0.8923***	-0.8934***	-0.9168***
	(0.000)	(0.000)	(0.000)	(0.000)
Black, Non-Hispanic	2.0110***	2.0346***	1.9808***	2.0073***
	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic	1.1007***	1.1147***	1.1554***	1.1312***
	(0.000)	(0.000)	(0.000)	(0.000)
Other	-0.6014***	-0.6559***	-0.6376***	-0.6775***
	(0.000)	(0.000)	(0.000)	(0.000)
Some HS	0.2013	0.2423	0.1062	0.1409
	(0.336)	(0.289)	(0.652)	(0.571)
HS	0.2533	0.2481	0.2225	0.2113
	(0.157)	(0.206)	(0.289)	(0.336)
Some College	0.2202	0.1905	0.2004	0.1511
	(0.248)	(0.359)	(0.365)	(0.509)
BA	-0.8724***	-0.9118***	-0.9150***	-0.9504***
	(0.000)	(0.000)	(0.000)	(0.000)
Income 15k - 20k	-0.3532*	-0.3173	-0.3911**	-0.3885*
	(0.057)	(0.125)	(0.044)	(0.059)
Income 20k - 25k	-0.6778***	-0.6429***	-0.7407***	-0.7065***
	(0.000)	(0.000)	(0.000)	(0.000)
Income 25k - 35k	-0.6850***	-0.6895***	-0.7216***	-0.7398***
	(0.000)	(0.000)	(0.000)	(0.000)
Income 35k - 50k	-0.6218***	-0.6085***	-0.7126***	-0.6962***
	(0.001)	(0.004)	(0.001)	(0.002)
Income 50k - 75k	-0.6588***	-0.5945***	-0.6998***	-0.6436***
	(0.000)	(0.001)	(0.000)	(0.001)
Income > 75k	-1.2361***	-1.1860***	-1.2885***	-1.2458***
	(0.000)	(0.000)	(0.000)	(0.000)
Not Reported	-1.2941***	-1.2500***	-1.2944***	-1.2660***
	(0.000)	(0.000)	(0.000)	(0.000)
gCOLA	-0.0113**	-0.0107*	-0.0067	-0.0070
	(0.046)	(0.067)	(0.171)	(0.188)
Transit (%)	-0.2265	-0.3447	-1.0253	-1.7167
	(0.852)	(0.805)	(0.403)	(0.277)

Table 4 Continued

Density	-0.0003	0.0000	0.0005	0.0008
	(0.467)	(0.966)	(0.309)	(0.193)
Pop (100k)	-0.0005	-0.0016	-0.0031	-0.0036
	(0.827)	(0.463)	(0.205)	(0.144)
Water Area (%)	0.2251	0.3373	0.0517	0.2214
	(0.547)	(0.422)	(0.892)	(0.619)
Coastal	-0.2795*	-0.3106	-0.3737**	-0.4356*
	(0.077)	(0.102)	(0.043)	(0.056)
Elevation	-0.1485***	-0.1556***	-0.1137***	-0.1034**
	(0.000)	(0.000)	(0.008)	(0.033)
Parkland (%)		-0.0016		0.0079
		(0.884)		(0.517)
Jan	-0.0135***	-0.0142***	-0.0076*	-0.0075
	(0.000)	(0.001)	(0.073)	(0.135)
July	0.0153*	0.0215**	0.0272***	0.0310***
	(0.059)	(0.028)	(0.001)	(0.001)
JanSun			-0.0150***	-0.0162**
			(0.003)	(0.011)
JulySun			-0.0030	-0.0027
			(0.706)	(0.742)
Precip	0.0066**	0.0057	0.0023	0.0019
	(0.046)	(0.130)	(0.567)	(0.627)
Observations	191,215	149,430	161,763	138,763
CBSAs	110	62	78	54
adj. R^2	0.0733	0.0757	0.0739	0.0759
F	279.52	364.36	450.72	591.95
p>F	0.0000	0.0000	0.0000	0.0000

Table 4 summarizes the relative importance of the city characteristics with statistically significant coefficient estimates by calculating the effect of a one standard deviation shift in these variables on BMI.[25] The combined effect of a milder climate (both January and July temperatures) is larger than the effect of elevation. The magnitude of the effects of climatic and topographic variation can be appreciated by comparing a continuous change in these variables to a change in income or education category. Further, these estimated changes in BMI associated with a 1 standard deviation change in the city characteristic are compared to changes in income or educational categories in Table 5.

Table 5 demonstrates the estimated change in BMI associated with variation in city characteristics compared to effects on BMI of changes in income or educational attainment. For

[25] We do not include Coastal in either Table 4 or Table 5 for multiple reasons. This variable is not continuous and as a referee pointed out, and while our use of Coastal here is a proxy for "flatness" of the city, Coastal could measure other natural amenities.

Table 5: Importance of Climate and Topography on Obesity

(A) Direction	(B) City Characteristic	(C) Estimated Coefficient	(D) Standard Deviation	(E) Estimated Change in BMI (C) * (D)
	Topography			
Increase	Elevation	-0.15	1,400 feet	-0.21
	Urban			
Increase	gCOLA	-0.01	11%	-0.13
	Climate			
Increase	Jan	-0.01	12 degrees (F)	-0.16
Decrease	July	0.02	6 degrees (F)	-0.09
Decrease	Precip	0.01	15 inches	-0.10

example, the reduction in BMI associated with an increase in elevation of 1,400 feet (a 1 standard deviation increase) is equivalent to 3/4of the estimated reduction in BMI if income (a categorical variable) changed from (15k-20k) to (35k-50k). Thus, an elevation increase of 1,750 feet achieves the same effect as if an individual's income category increased. However, an increase in elevation of 1,440 feet is associated with only 1/5 of the estimated reduction in BMI as from a change in education from High School to College.

Table 6: Importance of Climate and Topography (Table 3 Model 1 estimates)

Direction	City Characteristic	Standard Deviation	Proportion of Reduction in BMI Compared to an Income Change of (15k-20k) to (35k-50k)
Increase	Elevation	1,400 feet	77%
Increase	gCOLA	11%	47%
Increase	January_Avg8110	12 degrees (F)	61%
Decrease	July_Avg8110	6 degrees (F)	34%
Decrease	Precip_Annual8110	15 inches	37%

Direction	City Characteristic	Standard Deviation	Proportion of Reduction in BMI Compared to an Education Change of (High School) to (College)
Increase	Elevation	1,440 feet	18%
Increase	gCOLA	11%	11%
Increase	January_Avg8110	12 degrees (F)	15%
Decrease	July_Avg8110	6 degrees (F)	8%
Decrease	Precip_Annual8110	15 inches	9%

6. ROBUSTNESS CHECKS

As noted above, mesomorphs tend to have higher BMI due to greater muscle mass. The presence of mesomorphs works against finding differences in the spatial distribution of BMI based on amenities because their amenity preferences are similar to ectomorphs. To minimize the influence of the mesomorphs, the first robustness check estimates equation (5) using a logit model where b_i is now a binary indicator variable equal to 1 if the person is obese or 0 if the person has normal weight. This estimation excludes underweight or overweight individuals, attempting to keep only ectomorphs and endomorphs in the estimation. Results are reported in Table 6. Demographic, educational, and income characteristics are strongly related to the incidence of obesity. Grocery cost (*gCOLA)* is negatively related to obesity.

City amenities, such as higher elevation and mild January (*Jan*) and July temperatures (*July*) are strongly statistically significant explanatory variables for obesity and act in the expected direction based on theory and previous research. In addition, there is some evidence that housing density (*Density*) is negatively related to obesity, as perhaps urban cores with high density may be more walkable. Overall, the results using an obesity indicator as the dependent variable are similar in sign and significance to the empirical tests using BMI.

Other robustness checks add additional variables to the specifications reported in Table 3. Adding skill intensity (% BA) as a proxy for city amenity to the models from Table 3 does not alter our conclusions regarding the effect of climate and topographic variables, except that the estimated effect of July temperatures is lower and sometimes not significant. Separately, we include measures of behaviors (smoking, drinking) and find that after controlling for these factors the effects of individual and area characteristics are, if anything, larger in magnitude and similar in significance.

The theoretical relation between amenity characteristics and BMI is consistent with two possible mechanisms for achieving spatial differences in BMI. One possibility is a migration effect, in which individuals with a natural tendency towards obesity are more likely to move to areas with amenities for the obese. Second is an adaptation effect, in which the population adapts to the amenities in the surrounding area. The adaptation argument suggests that individuals born in an area will adjust to conditions through childhood and that differences in age-adjusted BMI should not vary with amenity factors. The migration effect suggests that individuals who have reached an age where they control moving decisions are likely to change location based on amenities.

A partial test of these two possibilities is to determine if the differences associated with the amenity variables in Table 3 are robust to age differences. This test was performed by interacting the Z_k climate amenity variables in equation (5) with dummy variables for age < 25 to determine if the amenity effects differ among individuals who likely were born in the city and adapted rather than having migrated there as adults. In the interest of brevity, the findings can be stated.[26] The results reported in Table 3 are robust to differentiation by age < 25 in that none of the terms with amenity interacted with age < 25 are statistically significant. This suggests that, even without adult migration, differences in BMI associated with amenity variables are substantial. Put another way, the large climatic and topographic effects on BMI are not due to migration of adults selecting areas but either to past migration or to environmental adaptation. Consistent with this position, Glaeser and Tobio (2008) find that the growth of cities in the U.S.

[26]Results are available from the authors upon request.

Table 6: Empirical Results (Dependent Variable – Binary Obesity Indicator)

	1	2	3	4
Age	0.1270***	0.1280***	0.1268***	0.1282***
	(0.000)	(0.000)	(0.000)	(0.000)
Age^2	-0.0010***	-0.0010***	-0.0010***	-0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.5910***	-0.5983***	-0.5948***	-0.6058***
	(0.000)	(0.000)	(0.000)	(0.000)
Black, Non-Hispanic	0.7883***	0.7932***	0.7784***	0.7878***
	(0.000)	(0.000)	(0.000)	(0.000)
Hispanic	0.4813***	0.4915***	0.4918***	0.4936***
	(0.000)	(0.000)	(0.000)	(0.000)
Other	-0.3186***	-0.3376***	-0.3226***	-0.3346***
	(0.000)	(0.000)	(0.000)	(0.000)
Some HS	-0.2304**	-0.2568**	-0.2563***	-0.2583**
	(0.011)	(0.011)	(0.008)	(0.013)
HS	-0.2074**	-0.2362***	-0.1939**	-0.2051**
	(0.013)	(0.009)	(0.033)	(0.031)
Some College	-0.2209**	-0.2569***	-0.2080**	-0.2328**
	(0.010)	(0.005)	(0.030)	(0.018)
BA	-0.6865***	-0.7222***	-0.6779***	-0.6930***
	(0.000)	(0.000)	(0.000)	(0.000)
Income 15k - 20k	-0.0293	-0.0225	-0.0451	-0.0438
	(0.659)	(0.758)	(0.533)	(0.560)
Income 20k - 25k	-0.1100**	-0.1027**	-0.1347***	-0.1305***
	(0.012)	(0.026)	(0.003)	(0.005)
Income 25k - 35k	-0.0901	-0.0847	-0.0815	-0.0839
	(0.256)	(0.342)	(0.367)	(0.388)
Income 35k - 50k	-0.0249	-0.0266	-0.0468	-0.0474
	(0.635)	(0.649)	(0.411)	(0.441)
Income 50k - 75k	-0.0787	-0.0581	-0.0826	-0.0710
	(0.130)	(0.311)	(0.150)	(0.246)
Income > 75k	-0.2846***	-0.2689***	-0.3035***	-0.2916***
	(0.000)	(0.000)	(0.000)	(0.000)
Not Reported	-0.3608***	-0.3511***	-0.3546***	-0.3517***
	(0.000)	(0.000)	(0.000)	(0.000)
gCOLA	-0.0032*	-0.0028	-0.0022	-0.0022
	(0.095)	(0.158)	(0.267)	(0.277)
Transit (%)	-0.2169	-0.3162	-0.4099	-0.5565
	(0.647)	(0.540)	(0.412)	(0.361)

Table 6 Continued

Density	-0.0002*	-0.0001	-0.0000	0.0001
	(0.067)	(0.480)	(0.833)	(0.828)
Pop (100k)	0.0004	-0.0000	-0.0004	-0.0005
	(0.664)	(0.969)	(0.694)	(0.605)
Water Area (%)	0.2067	0.2053	0.1551	0.1774
	(0.119)	(0.182)	(0.289)	(0.296)
Coastal	-0.0993*	-0.1053	-0.1177*	-0.1273
	(0.066)	(0.101)	(0.075)	(0.122)
Elevation	-0.0553***	-0.0544***	-0.0495***	-0.0486***
	(0.001)	(0.002)	(0.002)	(0.009)
Parkland (%)		-0.0005		0.0010
		(0.888)		(0.834)
Jan	-0.0043***	-0.0045***	-0.0030*	-0.0032
	(0.002)	(0.003)	(0.073)	(0.114)
July	0.0066**	0.0089***	0.0095***	0.0111***
	(0.018)	(0.010)	(0.002)	(0.002)
JanSun			-0.0033*	-0.0033
			(0.088)	(0.168)
JulySun			-0.0002	-0.0005
			(0.947)	(0.883)
Precip	0.0021*	0.0020	0.0016	0.0012
	(0.080)	(0.121)	(0.240)	(0.383)
# Obs	120475	94133	101942	87418
# CBSAs	110	62	78	54
pseudo R-sq	0.0908	0.0930	0.0907	0.0929
chi-sq	6416.6555	8043.3036	9128.7255	15836
p>chi-sq	0.0000	0.0000	0.0000	0.0000

Sunbelt has little to do with the sun. The results in this paper may be responses to these amenity factors that begin in youth or genetic selection from the past. Heterogeneity is related to differences in the resident population rather than based primarily on differential migration of adults.

7. CITY-PAIR EXAMPLES

This section explores the city-pairs mentioned previously to determine the relative importance of city amenities or city population characteristics in accounting for the large differences in BMI, which is a novel contribution to the economics of obesity literature. The estimation results found in Table 3 Model 1 allow these relative effects of amenity and non-amenity factors to be compared. The city pairs are selected based on the observation of significant differences in average BMI, and the comparison is restricted to those variables with statistically significant estimated coefficients.

These statistically significant variables are grouped into categories such as climate, which includes January and July temperatures, and annual precipitation. We calculate the difference in each climate characteristic between the two cities and then multiply this difference by that characteristic's respective estimated coefficient. For example, Detroit has a January temperature of 25.60 degrees Fahrenheit while San Francisco is relatively warm at 50.80, a difference of 34 degrees Fahrenheit. Multiplying this difference by the estimated coefficient for January temperatures yields an estimate that BMI will be 0.34 units lower in San Francisco compared to Detroit due to San Francisco's relatively warmer January. For individual characteristics, we aggregate these to the city level using survey methods and perform similar calculations. For both, we aggregate the resulting estimates up to their respective category. Continuing with our climate example, we estimate that BMI will be 0.24 (0.08) units lower in San Francisco because of San Francisco's milder July temperatures (less precipitation). In aggregate, we estimate that the BMI of San Francisco will be 0.67 units lower than Detroit due to its favorable climate. Further, we calculate using survey methods that Detroit's average BMI is 28.93 compared to San Francisco's 26.89, a difference of 2.04 units. Because climate differences between San Francisco and Detroit can explain approximately 0.67 units of this difference, we conclude that these climate differences explain approximately 33 percent of the difference in BMI between these two cities.

San Francisco and Detroit, presented in the first panel of Table 7, have very different BMI and population characteristics. Nevertheless, city characteristic differences explain 26 percent of the difference in BMI between these cities compared to demographic, education, and income differences that in total explain 20 percent. St. Louis and Honolulu differ significantly in both amenity and population characteristics. This results in a very large BMI difference. In this case, demographic differences are influential but city amenities explain as much as individual characteristics. The third city pair, Pittsburgh and Denver, has differences in BMI similar to St. Louis and Honolulu but their population characteristics are not as dissimilar. As a result, the city amenity effects on BMI are far more important than the non-amenity variables in explaining the large BMI difference. The preceding city-pair examples demonstrate that city-amenities, both topographic, and climatic, can explain as much or more of the differences in BMI among cities as differences in individual characteristics such as age, income, education, ethnicity, and race.

8. CONCLUSIONS

Our initial goal was to determine whether the substantial differences in obesity across cities are due to effects associated with observable population characteristics known to explain BMI differences among individuals or if city amenities, particularly climate, are also important. The answer is clear. While differences in individual income, education, age, race, ethnicity, and gender play a role in intercity variation in BMI, specific city amenity characteristics also matter.

Furthermore, the influence of climate and other amenity characteristics agrees well with prior expectations based on physiological effects of various city amenities. The empirical results confirm the differential attraction for persons of healthy or obese weight to local area temperatures. Topography and elevation are also influential. Food prices even play the expected role. The influence of these factors is not only statistically significant, it is of practical significance in comparison to factors such and income and education. For example, the estimates imply that a small shift in July average temperatures can affect BMI as much as doubling (or perhaps tripling) of income along a certain income range.

Table 7: City-Pair Examples (Table 3 Model 1 Estimates)

City Pair: Detroit, MI & San Francisco, CA		
	Detroit	San Francisco
Average BMI	28.93	26.89
Significant Variables	Raw Difference	Percent of Difference
Topography	-0.09	-4.53%
Climate	0.67	32.71%
Demographics	0.23	11.38%
Education	0.13	6.20%
Income	0.01	0.70%
Summary		
City Amenities Explain:	0.58	28.18%
Indv. Characteristics Explain:	0.37	18.27%
City Pair: St. Louis MO & Honolulu, HI		
	St. Louis	Honolulu
Average BMI	28.94	27.29
Significant Variables	Raw Difference	Percent of Difference
Topography	0.20	12.17%
Climate	0.70	42.12%
Demographics	0.71	42.70%
Education	0.03	1.68%
Income	-0.02	-1.34%
Summary		
City Amenities Explain:	0.90	54.29%
Indv. Characteristics Explain:	0.71	43.04%
City Pair: Pittsburgh, PA & Denver, CO		
	Pittsburgh	Denver
Average BMI	29.06	27.26
Significant Variables	Raw Difference	Percent of Difference
Topography	0.61	33.62%
Climate	0.17	9.30%
Demographics	0.18	9.96%
Education	0.08	4.47%
Income	0.05	2.86%
Summary		
City Amenities Explain:	0.77	42.91%
Indv. Characteristics Explain:	0.31	17.30%

An attempt to determine if differential migration is important in determining the relation between city characteristics and BMI found that there were no differential effects of these characteristics on those under 25, i.e. those less likely to have migrated in response to city differences. This is not a very strong test and leaves open the question of the influence of past migration by those with a hereditary tendency toward obesity. In sum, the question of whether these results reflect differential migration of individuals into locations or adaptation of identical individuals to different local conditions will require additional research. This is a very consequential question because, if the association is based on adaptation, it means that increasing global temperatures will lower obesity.

The results raise concerns regarding omitted variables bias in economic research. BMI is generally not observed, but it is correlated with important observable individual characteristics, particularly education and income, and it also varies with a variety of city amenities. Both categories of variables are important in empirical studies. For example, studies of intercity wage or productivity differentials include personal characteristics and city amenity variables. Because these variables are correlated with omitted BMI, the effect of BMI on wages may bias estimates of the effects of education and city amenity on wages. City quality of life measures allow wages of residents to vary due to education. However, they assume that local amenity based on climate and topography does not select population based on factors like obesity that influence wages and productivity. It appears that the potential for unobserved differences in BMI to play a role in determining the way wages and productivity vary over space limits the ability to construct measures of wage differentials across cities for individuals who are otherwise observationally equivalent.

One application of the climate results is to the finding by Sinha and Cropper (2015) that household willingness to pay for warmer winters has a strong negative correlation with willingness to pay for warmer summers. The empirical results here confirm these effects as the attractive effects of winter and summer temperature carry opposite signs in the BMI and obesity equations. This reflects the preference structure of the endomorphs who are less bothered by winter cold may have higher aversion to summer heat. Conversely, ectomorphs are relatively more sensitive to winter cold but have less aversion to summer heat. Given the result that endomorphs sort into areas with colder winters, it follows that warmer winters due to climate change should generate smaller benefits, while selection of endomorphs into areas with cooler summers should make warming in these areas costly. Thus, the sorting of population reported here causes the willingness to pay to avoid the warmer winters and summers associated with climate change to be larger than would be the case if BMI were distributed uniformly over space.

Overall, spatial sorting based on BMI, which has received little attention in the literature, may have significant implications for empirical research and should be considered a possible source of omitted variable bias.

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