WHO IS FIT IN AMERICA? A SPATIAL ANALYSIS OF SOCIO-DEMOGRAPHIC INDICATORS RELATED TO A HEALTHY BODY MASS INDEX

THESIS

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INTRODUCTION

Data suggest that the U.S. population is overweight and getting heavier at a drastic rate. According to the Centers for Disease Control's annual Behavioral Risk Factor Surveillance System (BRFSS), the percent of the U.S. population considered obese rose from 15.9% in 1995 to 25.1% in 2006 (CDC 2006).

Table 1. Percent Fit/Overweight/Obese 1995 – 2006

	Healthy	Overweight	Obese
1995 (n = 49)	47.9	35.5	15.9
2006 (n = 51)	38.2	36.5	25.1

Source: CDC Behavioral Risk Factor Surveillance System 2006

The National Health and Nutrition Examination Survey (NHANES) which obtains its data via mobile clinical evaluations (in contrast to the self-reported data of the BRFSS) reports even higher numbers: 64.5% of adults were reported to be overweight in 1999-2000. Alarmingly, adult obesity has surged from 14.5% in 1971 to over 30% of the population in 1999-2000 after remaining somewhat constant for the previous twenty years (Flegal et al. 2002). While the prevalence rates differ across sex and ethnicity, no segment of the population has remained unaffected. Increases were reported among men and women in all age groups and across all ethnicities (Flegal et al. 2002). Such a dramatic increase has prompted public officials to view the frequency of overweight and obesity as both an epidemic and a public health issue. The surgeon general has said, "Overweight and obesity may not be infectious diseases, but they have reached epidemic proportions in the United States.... Left unabated, overweight and obesity may soon cause as much preventable disease and death as cigarette smoking." (HHS 2001, xiii)

In response to the Surgeon General's call to action (HHS 2001) researchers across disciplines have investigated a variety of correlates between obesity and diet (Wright et al. 2004), automobile dependence (Lopez-Zettina 2005) and community design (Frank et al. 2004; Sallis et al. 2004; Saelens et al. 2003; Ewing et al. 2003; McCann and Ewing 2003). The community design studies investigate an intriguing connection between urban ecology and obesity wherein it is suggested that residents are discouraged or encouraged to participate in physical activity based on the local built environment to such an extent as to have a public health outcome. So, while a large body of research explores how the urban form might influence fitness-related behavior, there have been no similar examinations of the characteristics of the fit population vis-à-vis place. This study's purpose, therefore, is to explore the demography of fitness in America, and furthermore to understand what the context of place can reveal about the reality of being fit in America.

While there are many potential paths to a healthy BMI, it is arguable that a healthy BMI is a high-likelihood outcome of fitness behavior. To be said another way, while many factors might contribute to a healthy BMI, it is unlikely that an individual who actively engages in regular, vigorous exercise will have an unhealthy BMI. This study therefore hypothesizes that a higher relative proportion of the population with a healthy BMI can be constructed as a measurable outcome for fitness-related activity; and, more precisely, that the *rate* of fit people per a given unit of population can be described as a *risk factor* for affirmative, chosen physical activity. So, after examining the obesity "epidemic", can we identify its obverse –who is fit in America?

If we revisit the national statistics we find that a little less than 1/3 of the population overall has a healthy BMI. When examined by age cohort, however, we find that the risk factor for *fitness* decreases with age (Table 2). With such figures in mind we can posit that barring conscious effort to the contrary, non-fitness has become the inevitable or default condition for Americans. Maintaining fitness has thus become the questionable behavior.

Table 2. Distribution of BMI Categories (in %) by cohort (BRFSS 2006)

	Underweight	Fit	Overweight	Obese	N
Under 18	2.83	47.83	34.99	14.35	2,118
18 to 24	4.17	53.38	26.27	16.17	14,570
25 to 29	2.53	43.89	31.56	22.02	17,062
30 to 39	1.60	38.96	33.57	25.88	48,310
40 to 49	1.38	35.94	35.77	26.91	64,063
50 to 59	1.16	31.63	37.38	29.83	71,381
60 to 69	1.35	30.27	39.64	28.74	55,855
70 to 79	2.03	35.43	40.31	22.23	40,858
Over 80	3.70	48.36	35.01	12.93	22,144
Total	1.780	36.505	36.310	25.405	
N	5,987	122,787	122,134	85,453	336,361

Until one reaches the age of 25 one has a greater than 50% *risk* for being fit. That 50% risk factor is roughly equivalent to the overall population in only the fittest cities in America. After age 30 fitness rates begin to drop quickly but no age cohort's fitness risk is as poor as the unhealthiest cities in America. Such an unequal spatial distribution of the healthy population prompts us to ask why the people in some cities are fit while others are not. Furthermore, these spatial differentials give us an opportunity to identify other socio-demographic, place and economic variables together with fitness rates to gain a better understanding of what constitutes “fit” in America.

CHAPTER 1

BACKGROUND AND STRUCTURE

If a mere third of the adult population can claim a healthy Body Mass Index, then what is it that enables this lucky few to be so classified? An opportunity to understand the answer to that question is revealed in a map of the spatial variation of fitness (Figure 1). Particularly one will notice that fitness is not evenly distributed across the country. Certain regions stand out as having proportionally more fit people than others (e.g., the upper Northeast and the Intermontane West).

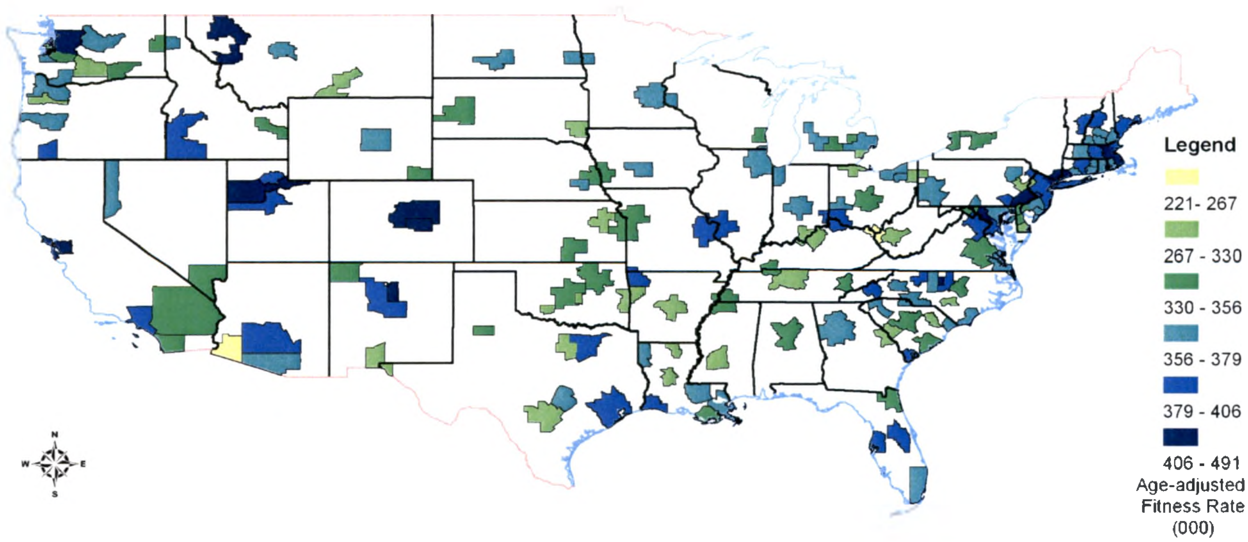


Figure 1. MMSAs by Age-Adjusted Fitness Rate

The spatial variation in fitness suggests a possible similar spatial variation in environmental, economic, social and demographic indicators. To investigate those possible correlates this study will use the MMSA as the sampling unit for various indicators and the variation among them as a method for understanding the characteristics of that population who remains fit. My research question can thus be stated directly as, what are the social, economic and demographic characteristics of the fit in America?

This study does not expect that population, place or environmental variables can *predict* whether the population will be fit. While there may be associated characteristics between places and the fitness of their populations, it will be difficult to over simplify the causes of obesity so hygienically as to say that "San Franciscans are fit because they spend less time in their automobiles" or the like. So, rather than *causes* of fitness this study is generally motivated to understand what the variation in fitness rates indicates about what it means to be fit in America. Likewise this study does not examine the relationship between place and fitness as a product of unitary causation or determination. Rather it uses the understood character of place to shed light on the characteristics of the fit population.

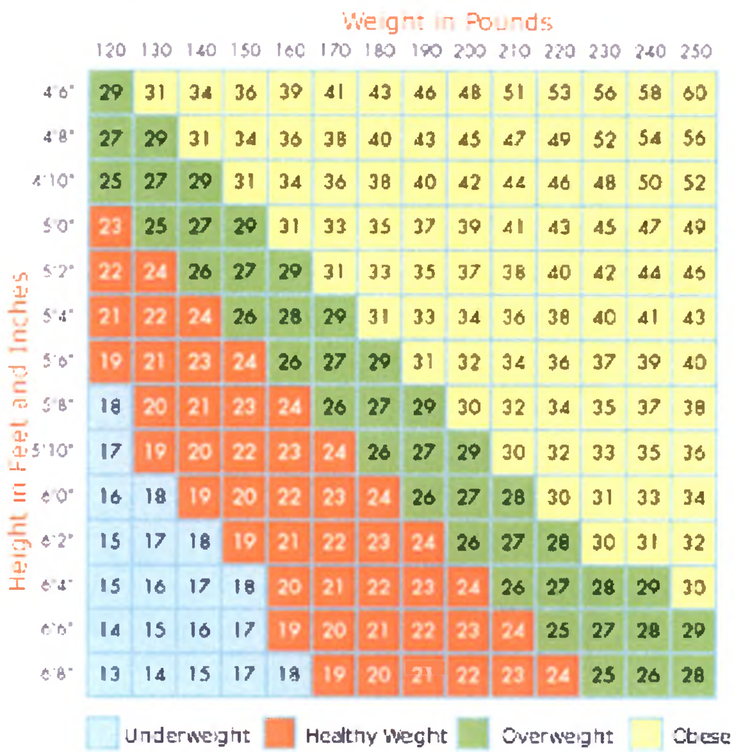
Defining Fit, Overweight and Obese

The Body Mass Index (BMI), or the eponymous Quetelet's Index after the Belgian mathematician who devised it, measures the ratio of a person's weight in kilograms to his/her height in meters squared. The use of Quetelet's index has become the standard, international measurement of a healthy, overweight or obese body weight (NIH 1998) based on Quetelet's own thresholds (Table 3).

Table 3. BMI and Weight Status (CDC 2006b)

BMI	Weight Status
< 18.5	Underweight
18.5 – 24.9	Fit
25 – 29.9	Overweight
> 30	Obese

BMI can also be calculated using height in inches and weight in pounds according to the formula: $BMI = \dfrac{weight(lbs.)}{height(in.)^2 * 703}$. Figure 2 (below) shows BMI ratios pre-calculated for a range of height (ft and in.) and weight (lbs).



	120	130	140	150	160	170	180	190	200	210	220	230	240	250
4'6"	29	31	34	36	39	41	43	46	48	51	53	56	58	60
4'8"	27	29	31	34	36	38	40	43	45	47	49	52	54	56
4'10"	25	27	29	31	34	36	38	40	42	44	46	48	50	52
5'0"	23	25	27	29	31	33	35	37	39	41	43	45	47	49
5'2"	22	24	26	27	29	31	33	35	37	38	40	42	44	46
5'4"	21	22	24	26	28	29	31	33	34	36	38	40	41	43
5'6"	19	21	23	24	26	27	29	31	32	34	36	37	39	40
5'8"	18	20	21	23	24	26	27	29	30	32	34	35	37	38
5'10"	17	19	20	22	23	24	26	27	29	30	32	33	35	36
6'0"	16	18	19	20	22	23	24	26	27	28	30	31	33	34
6'2"	15	17	18	19	21	22	23	24	26	27	28	30	31	32
6'4"	15	16	17	18	20	21	22	23	24	26	27	28	29	30
6'6"	14	15	16	17	19	20	21	22	23	24	25	27	28	29
6'8"	13	14	15	17	18	19	20	21	22	23	24	25	26	28

Figure 2. BMI by Height and Weight

It should be noted that there is some controversy surrounding the use of the BMI as a measure of adiposity or body fat. Logically it makes sense that a simple ratio of weight to height would normalize variation in body composition among different individuals. For example a 6' 4" 240 pound professional football linebacker would be on the threshold between overweight and obese as would a 6' 4" 240 pound football fan. The football player who might be carrying a body fat percentage in the low teens could argue against his BMI as being indicative of obesity. Indeed a body of clinical research has addressed the use of the BMI as an indicator of adiposity and therefore obesity. Studies have found that while waist measurement *combined* with BMI gives a better picture of adiposity, BMI is remarkably accurate at predicting obesity (Gallagher et al. 1996). The Gallagher study also examined the potential racial/ethnic bias in the use of the BMI and found no significant distinction between adiposity between individuals of different races. For the sake of consistency with the existing literature this study will use the same measure as the indicator of fitness/overweight/obesity.

Study Area

This study will examine the population of the United States and will use 166 selected Metropolitan/Micropolitan Statistical Areas or Metropolitan Divisions (MMSAs) as the sampling units. The MMSAs selected were those which the CDC's annual Behavioral Risk Factor Surveillance System (BRFSS 2006) reports results for the question "Weight classification by Body Mass Index (BMI)". Data are reported at the State and MMSA scale. The MMSA is a geographic classification defined according to the standards set by the Office of Management and Budget (OMB 2000) and first used by the Bureau of the Census in 2003:

- Metropolitan statistical area — Group of counties that contain at least one urbanized area of 50,000 or more inhabitants (e.g., Atlanta-Sandy Springs-Marietta, GA)
- Micropolitan statistical area — Group of counties that contain at least one urban cluster of at least 10,000 but less than 50,000 inhabitants (e.g., Willimantic, CT)

- Metropolitan division — A smaller group of counties within a metropolitan statistical area of 2.5 million or more inhabitants. For example, the Dallas-Ft. Worth-Arlington Metropolitan statistical area contains two metropolitan divisions: Dallas, TX and Ft. Worth-Arlington, TX.

Twenty-five MMSAs were not reported in 2006 and so their data were pulled forward from the most recent year before 2006. No data earlier than 2000 were considered. Centers for Disease Control reports BRFSS data at the MMSA scale if and only if they have data for at least five hundred respondents in an MMSA. Because BRFSS survey clusters are developed at the state scale, many MMSAs do not include a sufficient number of respondents in order for data to be reported. For that same reason, data are not available at the county level. While it might be instructive to consider non-urban places together with urban places, the reporting of the BRFSS data is restricted to either the state or the MMSA scale. This study chose the MMSA scale because it offers a better scale for comparison than the state scale and because it offers more data points with greater variation.

Data

The dependent variable is the age-adjusted fitness rate of the population. The fitness rate (per 1000) is simply the percent of population reporting a healthy BMI (BRFSS 2006) times 10. Because the relationship between age and BMI is non-linear, the reported BMI rates have been age-adjusted using the indirect method. Age cohort population numbers at the MMSA scale are taken directly from the 2006 American Community Survey and the nationwide fitness rates by age cohort were calculated from the raw 2006 BRFSS data file. BRFSS suppresses the county identifiers for survey respondents to ensure confidentiality. As such, I could not calculate age-specific fitness rates at the MMSA scale and therefore could not use the direct method for age standardization. Please see Appendix D for a more details on age standardization.

Ranking Cities by BMI (BRFSS data)[1]

The Centers for Disease Control have conducted the BRFSS annually since 1984. The survey began as an effort to provide even, nationwide health data at the state level in the absence of consistent polling by the states. It has since grown to be the largest annual telephone survey in the world with over 350,000 respondents polled annually. Among the questions in the survey are questions pertaining to height and weight from which survey reports an aggregate, calculated Body Mass Index (BMI) for the population at the state and MMSA scale.

Using the percentage population with a "fit" BMI (within the range of 18.5 – 24.9) from the BRFSS data, Table 4 lists the 90th and 10th percentiles and ranks cities from most to least fit. A complete list of the 166 metropolitan areas from the 2006 survey is provided in Appendix B.

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[1] When viewing the list in rank-order it is important to consider the limits of the variation within the data. If we eliminate the top and bottom three cities, the range in fitness from top to bottom is a mere 14 percentage points (number 4, San Francisco with 46.5% and number 163, Nashville with 32.2%). If we look at the difference between those just outside the top and bottom 10th percentiles, the variation is even more constrained: a mere nine percentage point spread between the city ranked 18th and the one ranked 149th. Nine percent of the population moves a city from the 90th to the 10th percentile. One should therefore be careful when comparing one city with another in the rankings.

Table 4. Data Range 90th percentile

%ile	Metro Area	Rank	% Fit (2006)
90	Santa Fe, NM Metropolitan Statistical Area	1	51
90	Cambridge-Newton-Framingham, MA Metropolitan Division	2	50.5
90	Bethesda-Gaithersburg-Frederick, MD Metropolitan Division	3	47.1
90	San Francisco-Oakland-Fremont, CA Metropolitan Statistical Area	4	46.5
90	Bridgeport-Stamford-Norwalk, CT Metropolitan Statistical Area	5	46.2
90	Burlington-South Burlington, VT Metropolitan Statistical Area	6	46.1
90	Provo-Orem, UT Metropolitan Statistical Area	7	45.8
90	Salt Lake City, UT Metropolitan Statistical Area	8	45.7
90	Missoula, MT Metropolitan Statistical Area	9	45.4
90	Colorado Springs, CO Metropolitan Statistical Area	10	45.2
90	Boston-Quincy, MA Metropolitan Division	11	44.2
90	Hilo, HI Micropolitan Statistical Area	12	44.1
90	New York-White Plains-Wayne, NY-NJ Metropolitan Division	13	44
90	Denver-Aurora, CO Metropolitan Statistical Area	14	44
90	Kahului-Wailuku, HI Micropolitan Statistical Area	15	43.8
90	Honolulu, HI Metropolitan Statistical Area	16	43.7
90	Kalispell, MT Micropolitan Statistical Area	17	43.5
75	Philadelphia, PA Metropolitan Division	18	43.3
	...		
25	Salem, OR Metropolitan Statistical Area	149	34
10	Monroe, LA Metropolitan Statistical Area	150	33.8
10	Augusta-Richmond County, GA-SC Metropolitan Statistical Area	151	33.7
10	Jackson, MS Metropolitan Statistical Area	152	33.7
10	Detroit-Livonia-Dearborn, MI Metropolitan Division	153	33.5
10	Charleston, WV Metropolitan Statistical Area	154	33.5
10	Louisville, KY-IN Metropolitan Statistical Area	155	33.4
10	Allentown-Bethlehem-Easton, PA-NJ Metropolitan Statistical Area	156	33.1
10	Lawton, OK Metropolitan Statistical Area	157	33
10	Youngstown-Warren-Boardman, OH-PA Metropolitan Statistical Area	158	33
10	Seaford, DE Micropolitan Statistical Area	159	33
10	Fort Worth-Arlington, TX Metropolitan Division	160	32.8
10	Shawnee, OK Micropolitan Statistical Area	161	32.5
10	San Antonio, TX Metropolitan Statistical Area	162	32.3
10	Nashville-Davidson--Murfreesboro, TN Metropolitan Statistical Area	163	32.2
10	Yuma, AZ Metropolitan Statistical Area	164	28.6
10	Fayetteville, NC Metropolitan Statistical Area	165	28.6
10	Huntington-Ashland, WV-KY-OH Metropolitan Statistical Area	166	23.3

Source: CDC 2006a

CHAPTER 2

FIT PEOPLE AND FIT CITIES

The notion of "fit" or "fat" cities has come to the national consciousness through *Men's Fitness* magazine's annual survey of the twenty-five "fittest" and "fattest" cities. Following the tradition of rating places (with many of its attendant flaws) the annual survey began in 2000, the subtext of which is that the "size of your waistline might be a product of your zip code (Lucia 2006)." While the variability in the fit/obese population across cities in the United States gives objective legitimacy to the question, the *Men's Fitness* methods are questionable. The survey rates cities across the United States on a variety of factors from prevalence data for healthy/unhealthy food and drink, commute times, ratio of park land to population and others. The final product is a rank-order listing of the twenty-five "fittest" and twenty-five "fattest" cities in the United States.

While the purpose of this paper is not to criticize the *Men's Fitness* survey, the flaws in its method reveal an opportunity for better understanding the symbolic reality of "fitness" in America. One perplexing characteristic of the survey is its failure to consider the single variable from the BRFSS that really does indicate whether a city's population is "fit" or fat": Weight classification by Body Mass Index (BMI). Perhaps it should therefore be no surprise that a comparison of the *Men's Fitness* ratings with ranking by

BRFSS data is dissonant. For example, in the ranking of cities by the BRFSS data *Men's Fitness* number 1 fattest city in the 2006 survey (Chicago, IL – 1st quartile) is actually eleven places *higher* than the third fittest city of Virginia Beach, VA (2nd quartile). A deeper critique[2] is that ecological factors such as prevalence of fast food establishments, recreational opportunities, health food stores and others, which weigh heavily in their method, do not indicate use or disuse. It is tempting to think, for example, that the young, active, fit population of Austin, Texas is thin and fit because they are out jogging around the trails, riding their bicycles trough the hills and swimming at Lake Travis. It is likewise tempting to think that career-obsessed Houstonians are getting fat while they spend more hours per week in cars (and endure among the longest commute times in the country) driving on their thousands of miles of freeways. Indeed Houston is one of *Men's Fitness* perennial favorites for the fattest city in the nation owing precisely to its high number of vehicle miles traveled (VMT) and shocking density of fast food restaurants (the highest in the nation). Yet the BRFSS data rank Houston in the 75th

[2] Other critiques of the *Men's Fitness* survey that do not bear directly on this study should still be mentioned in the spirit of completeness. First, the study repeatedly fails to account for the modifiable areal unit problem. For example, their ratings de-couple Long Beach from Los Angeles and Ft. Worth from Arlington, TX. Many factors based on data from the Census Bureau and the Centers for Disease Control's Behavioral Risk Factor Surveillance System (BRFSS) influence the rankings. Unfortunately neither agency reports data for each of those geographies separately. The fact that Arlington and Long Beach appear in the list of fit cities while their principal cities of Fort Worth and Los Angeles appear in the list of fat cities is perplexing. A second problem is a stated reliance on non-authoritative sources of data. For example, prevalence data for fast food establishments or gymnasiums are established from yellowpages.com rather than from the Economic Census.

percentile (top 25 percent) of fit cities in the country compared with Austin who languishes in the 50^{th} percentile. Perhaps Houstonians drive past more often than Austinites drive through.

The bias in the ranking notwithstanding, a quick view of the *Men's Fitness* list reveals something deeper about the symbolic understanding of fitness in America. The perennially fit cities in their survey are those that symbolize the young, affluent and economically dynamic (Colorado Springs, San Francisco, Austin). By contrast, the perennially fat are older, economically depressed and more conservative (Detroit, Chicago, Oklahoma City, Cleveland). More importantly, cities are ranked less by objective measures than by their symbolic representations of "health" as understood and promulgated by a dominant social order (Silk and Andrews 2006).

CHAPTER 3

HEALTH, PLACE AND WALKABLE CITIES

Examinations of the connection between the ecology of city environments and the health of the population certainly have not been limited to the popular press. Under the rubrics of smart growth (McCann and Ewing 2003), air quality (Frank et al. 2004) and "quality of life" (Sallis et al. 2004) researchers have undertaken rigorous examinations of the possible connection between both the physical and social structure of modern American cities and the health of their people.

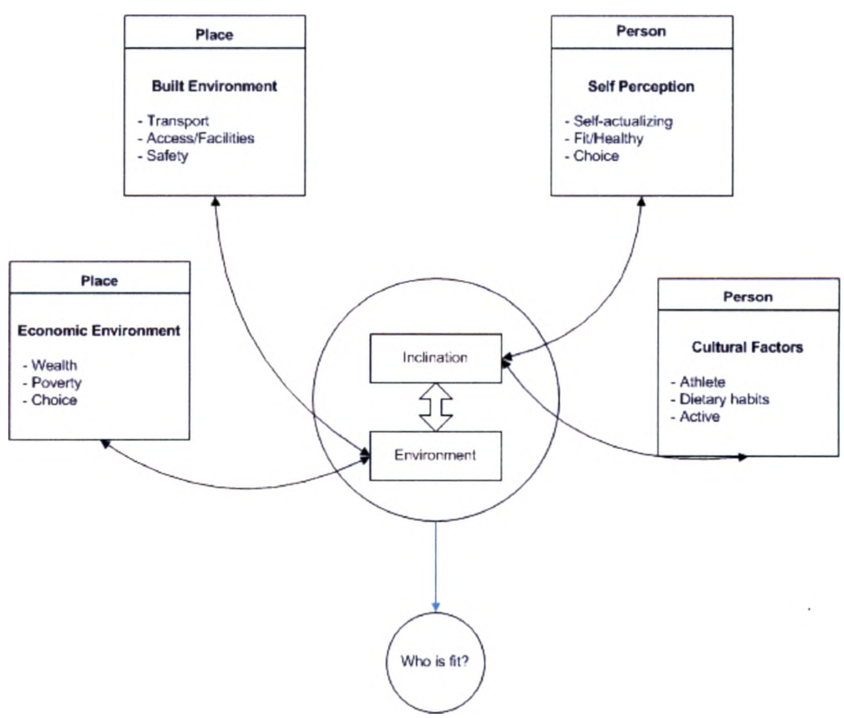


Figure 3. Fitness at the Intersection of Place and Person

While place-based correlates with health are eye-opening, conceptual understanding of health (be it fitness or any other health outcome) cannot be separated from the person (Figure 3). As such, identity theory together with conceptualizations of social agency and structure can provide a prism through which we can better understand the sometimes complex relationship between a person's health and his/her place. This study will show that it is not geography which *determines* one's fitness. Fitness is an individual decision and indeed one that the obesity trends suggest is an increasingly difficult one to make.

This study uses place, specifically the MMSA, as the sampling unit to understand the demographic correlates with a healthy BMI. From those demographic correlates, I attempt to draw some understanding of fitness posed by the intersection of place, demography and behavior. This study, therefore, does not fit neatly into a subfield of Geography. It draws upon the literature in urban geography, behavioral psychology, epidemiology, demography and physical cultural studies.

Fat Cities Make Fat People

Barring specific medical conditions, a healthy body weight is determined by a balance between caloric intake and expenditure (HHS 2001). To understand causes of obesity, many ecological studies have examined proximate causes for reductions in activity (caloric expenditure) or for increases in consumption. Concurrent with the upward trend in BMI, it has been found that caloric and carbohydrate macronutrient intake have increased in the last 30 years (Wright 2004). At the same time cities have grown larger but less dense (McCann and Ewing 2003), automobile dependence has increased (Pucher and Renne 2003), and a congruent correlative trend between urban density and frequency/distance of travel in a personal vehicle has emerged. For example, residents of downtown San Francisco report an average of 210 vehicle trips per person per year while residents of suburban Daly City and Walnut Creek report 730 and 900 respectively (Crane 2000). More importantly, correlations have been found between increases in vehicle miles traveled (VMT) and BMI (Lopez-Zetina et al. 2006; Pendola and Gen 2006; Frank et al. 2004). Such a connection makes sense if auto travel comes at the expense of physical activity to the extent that it drops energy expenditure below the level of caloric intake. That Americans take their cars over easily walkable distances is indisputable: nationally 66% of trips under one mile and 89% of trips under two miles are taken by car (Pucher and Renne 2003). The same study found that 41% of all trips (in 2001) were under two miles. On the caloric intake side of the equation, studies have found that residential location and access to grocery stores influences BMI. One study of the greater Los Angeles area found that those who travel to grocery stores via automobile –particularly to grocery stores in disadvantaged neighborhoods—have a higher BMI (Inagami et al. 2006). In such a light, the construction of the American human environment appears to have a powerful if elusive effect on the balance between caloric intake and expenditure. Even the reports of increased caloric intake have attributed some of the cause to an increase in meals taken away from home (Wright et al. 2004).

Environment as a Conditioning Agent

Much of the research on the correlates between the built environment and health can be framed on a theoretical conception of the built environment as a conditioning agent on its residents as specified, more generally, by B. F. Skinner (Boeree 2006). In this context, environment can therefore be examined to understand its determinants, proximally, on physical activity levels and, ultimately, on the balance between caloric intake and expenditure. Under a Skinnerian construct it is tempting to look for a *causal* relationship between the construction of habitat, transportation habits and body condition. The logical conclusion to draw from such a correlation is that physical activity decreases in proportion to the reduced opportunity to engage in physical activity. In the context of the research on urban environment and health, it suggests that because our cities are built for automobile transport to such an extent that they affirmatively discourage (for reasons of safety or discomfort) or outright preclude non-motorized transport (by introducing trip distances no longer practical), that transport-related physical activity will decline and, by extension, overall physical activity will decline thus tipping the balance in dietary energy toward a surplus. In other words, the environment-influenced decline in physical activity affects the energy expenditure side of the caloric balance equation and can thus be a causal factor for weight gain.

A view across all 166 MMSAs in this study reveals just such correlations. First one measure of "anti-sprawl" (population density per mile of road) is correlated with a higher rate of population with a fit BMI (Table 5). The same view likewise shows a correlation between an urban investment in green space (park density) and the risk for a fit BMI. No correlation was found between good air quality and a fit BMI, but such a finding is unsurprising when one remembers that dense cities tend to have fewer days with good air quality than do sprawling ones.

Table 5. Urban Ecological correlates with healthy BMI

	Age adjusted fitness rate
Population per mile of road	0.223
(p)	0.004
Park Density	0.269
(p)	0.001
% days AQI of "good"	0.014
(p)	0.858

Sources (in order): USDOT 2001, ESRI (appendix C), EPA 2007.

City Construction and Environmental Conditioning

The temporal correlation between de-densification of U.S. urban areas, increases in vehicle miles traveled and surging rates of overweight and obesity has prompted researchers to ask whether increased auto dependency (and, *ipso facto*, the urban transportation network) is a *cause* of the surging rates of overweight and obesity. Such causation is less conclusive. Perhaps one of the earliest and most influential studies derived a county-scale sprawl index from secondary, cross-sectional data and found a small but statistically significant relationship between sprawl and minutes walked, obesity, BMI and hypertension (McCann and Ewing 2003). McCann and Ewing's finding of a significant correlation between sprawl and BMI was corroborated by an examination of the SMARTRAQ (Strategies for Metropolitan Atlanta's Regional Transportation and Air Quality) data which found that mixed-land uses correlate with lower BMI (implying a greater frequency of walking for transport) and that *time* spent traveling by car increases the odds of obesity (Frank et al. 2004). Their findings were further strengthened by evidence of a direct correlation between increases in vehicle miles traveled (VMT) and BMI (Lopez-Zetina 2006; Lee and Friis 2006). Indeed similar findings remained significant even in the imminently walkable city of San Francisco (Pendola and Gen 2006) where population density was found to vary inversely with auto use and that those who express a preference for automobile transport report a higher average BMI.

City Organization, Transportation and BMI

The case implicating auto-dependent transport as a cause of obesity looks strong. If the one direction of the correlation between auto-dependent transport and obesity stands up to examination, then one must ask if the correlation is strong in the other direction. Do people living in walkable, less auto-dependent neighborhoods choose transport-related physical activity to a sufficient extent as to maintain a healthy BMI? The preceding is actually three questions that are better answered separately. First what, if any, ecological conditions encourage walking over driving. Second, given the existence of such conditions, do they result in a higher frequency of transport-related walking? Third does a higher frequency of transport-related walking result in a population with a lower BMI?

The answer to the first can be understood intuitively. City building on a northern European model of high density and mixed land use appears to correlate with a higher frequency of non-motorized transport appears to be correlated with the healthier northern European populations. Several studies have examined land use mix (LUM), connectivity and density as correlates for transport-related walking. Studies have found that mixed land uses offering a variety of destinations –particularly workplace destinations—is the best predictor of walking behavior (Cerin et al. 2006). Interestingly, the same study found that access to recreational facilities (parks, fitness centers etc.) has a much weaker effect on transport-related walking than does access to shopping and workplaces. An environment-scale comparison between a "high walkability" and "low walkability" neighborhood found that the residents of the "high walkability" neighborhood did indeed walk more, but that the difference evaporated once controls were introduced for age and education (Saelens et al. 2003). The findings of Cerin (2006) and Saelens et. al (2003) corroborate similar findings from Ewing (2003) and Frank (2004) that land use mix (LUM), particularly land use mix proximate to trip origins, is a strong indicator of a higher frequency of transport-related walking. So, the answer to the first question is that there are an identifiable set of ecological conditions which appear to encourage residents to walk.

The answer to the second question, "does a walkable environment actually get people out of their cars" is not quite as clear. A study of the San Francisco Bay area arrived at mixed results when answering this question (Cervero and Duncan 2003). By studying origin-destination pair trips, the study found that pedestrian/bicycle friendly neighborhoods do indeed show a mild correlation with a higher frequency of non-motorized transport. The same study found, however, that environmental factors such as time of day, rain and steepness of terrain have a more powerful *discouraging* effect on walking than do LUM or diversity of destinations to encourage walking. Cervero and Duncan's findings are corroborated by a study in the St. Louis area which suggests that individual perception of neighborhood and personal barriers to walking have a more powerful discouraging effect than sprawl (Joshu et al. 2008). Interestingly, Cervero and

Duncan found that even in pedestrian-friendly San Francisco auto transport dominates: 60.7% of trips under one mile and 87.5% of trips under five miles were taken by automobile. The San Francisco numbers for frequency of auto travel are not compellingly different from the national averages (66% of trips under one mile) (Pucher and Renne 2003). An obliquely-related but important finding in the Cervero and Duncan study (2003) is that after controlling for differences in car ownership, African-Americans, who are at far greater risk for obesity, took 82% *more* walking trips than their white counterparts. So while we can identify factors which encourage walking, it has not been demonstrated that the existence of such factors will actively discourage auto transport.

To summarize thus far, while early research suggested a strong connection between the auto-dependent environment and BMI, further research has failed to provide categorical support. A few idiosyncrasies in the early findings give some insight as to why the effect might not be very strong. First, even in dense, diverse, walkable cities, auto transport dominates (Cervero and Duncan 2003) while environmental factors do more to discourage walking than LUM (diversity of destinations) and density do to encourage walking. Second, the effect of the built environment to encourage walking is powerfully diminished when controlled for the education level of the population (Saelens 2003). Third, African-Americans demonstrate the highest prevalence of overweight and obesity (Flegal et al. 2002), yet have been found to walk significantly more than their relatively healthier white counterparts (Pendola and Gen 2006; Cervero and Duncan 2003). Perhaps most interesting are the findings from St. Louis that an affirmative response to "don't like exercise" had a high and significant odds ratio for predicting BMI and that age (45-65) had a high and significant beta (Joshu et al. 2008). To help resolve some of the ambiguity around the effect of sprawl on BMI the same study describes an interaction between county sprawl and personal barriers (e.g., injuries, fear of crime etc.). Where the number of personal barriers is low, sprawl has no influence on BMI; but as the number of personal barriers increases, the slope of the regression line between sprawl and BMI gets quite a bit steeper. Said another way, sprawl acts as a multiplier on the effects of personal barriers to exercising and therefore magnifies the effect of personal barriers to exercise.

Walkability, Fitness and Neighborhood Self-selection

More recent studies have discounted the simple correlation between sprawl and BMI. When one observes that, at the state level, Colorado and Utah have the lowest rates of obesity but among some of the highest sprawling counties (which are also their most populous) the correlation between sprawl and obesity seems counter intuitive. Reexaminations of the same question at a more refined scale have questioned whether the second direction of the correlation is strong: that building walkable cities will result in a population with a healthier BMI.

First, an examination of neighborhood self-selection as an explanation for the spatial variation in BMI found that those who tend toward obesity also tend to favor sprawling neighborhoods which do little to discourage auto transport –even to the exclusion of human powered transport (Eid et al. 2008). That study considered longitudinal data from the National Longitudinal Survey of Youth (NLSY79) and decomposed the simple correlation between sprawl and BMI. Importantly it showed the interaction to be weaker, if nonexistent, once controlled for age, sex and race. Among the more notable findings are that the sprawl index has no effect on BMI for women once controlled for race and age and that BMI is higher in high density, high land use mix (LUM) neighborhoods populated by blacks and Hispanics. Since the NLSY79 tracks address changes and because the 79% of the participants moved at least once during the study, the study can control for both observed and unobserved individual effects. What stands out is that the significant, negative correlation between BMI and LUM for men reflects a voluntary sorting of men with a lower propensity for obesity and residential preference for high LUM neighborhoods. Plantinga and Bernell (2007) similarly find that the correlation between sprawl and BMI is better explained by neighborhood self-selection: those with low BMI are more likely to select locations with dense development.

Perhaps one of the most compelling studies used a zip-code scale survey of height and weight data from drivers' license records in Chicago to compare socio-demographic data with the "fit" neighborhoods (Sööt et al. 2006). The study found that the inner ring of suburbs with a high sprawl factor had the fittest people as opposed to the low-sprawl, but poor and uneducated inner-city neighborhoods and the very high-sprawl exurban neighborhoods. The strongest correlation with fitness was a college degree. An expressed preference for driving and walking *both* varied directly with BMI; and, home ownership correlated with high BMI but with a lower significance. In light of these studies Frank (2007) has re-examined the SMARTRAQ data for neighborhood self-selection correlates with density, LUM and lower BMI and found corroborating evidence for the neighborhood self-selection factor: those who want to walk live in walkable neighborhoods, those who want to drive live in less-walkable neighborhoods.

The indictment of urban form as a cause for obesity is not entirely convincing. Granted, it can be shown that a correlation exists between fitness-friendly neighborhoods and the fitness of the residing population. Importantly, however, one cannot support a conclusion that the qualities of the neighborhood *promote* fitness beyond providing some desirable utility for a population that is already inclined to be fit –or more precisely, a population inclined to live in that neighborhood and be fit. The relationship between the urban ecology of "fitness" and the actual fitness of the population is therefore just muddied further. The question remains, then, who are the fit people in America? And what, if any, relationship exists between them and where they live?

CHAPTER 4

THE DENIZENS OF FIT CITY

To begin disentangling the relationship between place and fitness it is helpful to consider to the character of the fittest places. If we reconsider the 90^{th} percentile from the BRFSS rankings (Table 6) and characterize the cities by their access to recreational amenities and income, then the picture that emerges is one where recreational amenities merge with economic power.

Table 6. Fittest cities by amenities and income

Rank	City	Recreational Amenity	Income	% Fit
1	Santa Fe, NM	Sandia Mountains	$37,934	51.0%
2	Cambridge-Newton-Framingham, MA	Charles River	$47,168	50.5%
3	Bethesda-Gaithersburg-Frederick, MD		$48,697	47.1%
4	San Francisco-Oakland-Fremont, CA		$52,543	46.5%
5	Bridgeport-Stamford-Norwalk, CT		$67,269	46.2%
6	Burlington-South Burlington, VT	Lake Champlain, Adirondack Park	$27,551	46.1%
7	Provo-Orem, UT	Wasatch Mountains	$20,731	45.8%
8	Salt Lake City, UT	Wasatch Mountains	$32,133	45.7%
9	Missoula, MT	Bitterroot Wilderness	$30,608	45.4%
10	Colorado Springs, CO	Rocky Mountains	$33,569	45.2%
11	Boston-Quincy, MA	Charles River	$47,168	44.2%
12	Hilo, HI	Pacific Ocean, beaches	(unavailable)	44.1%
13	New York-White Plains-Wayne, NY-NJ	Central Park	$45,268	44.0%
14	Denver-Aurora, CO	Rock Mountains	$42,369	44.0%
15	Kahului-Wailuku, HI	Pacific Ocean, beaches	(unavailable)	43.8%
16	Honolulu, HI	Pacific Ocean, beaches	$36,828	43.7%
17	Kalispell, MT	Glacier National Park	(unavailable)	43.5%
	Mean National Income		$34,216	
	Median National Income		$33,529	

Each city in this list has either a high mean income, access to some of the best recreational amenities in the country, or both. At the extremes of either (amenities or wealth) the existence of one alone is sufficient to secure a city's place at the top. For example, neither Stamford, CT nor Bethesda, MD are known for any particular recreational amenity but Stamford, with the highest per capita income (indeed double the median), and Bethesda, (including Chevy Chase) which houses the nation's power elite, both sit atop the economic hierarchy of the United States. Similarly Burlington, VT (with a very low per capita income) whose University of Vermont students, faculty and staff look at the Adirondack mountains across Lake Champlain and Kahului-Wailuku, HI situated on a paradaisal, tropical landscape, each represent the pinnacle of recreational amenities available to an American. One extreme symbolically and materially represents power and, one can assert, social dominance. The other, as amenity spaces with no real economic power, represents the top of residential self-selection. Among the fit cities in-between power and preference are those where each exists in some proportion with the other. For example, Cambridge, MA is both wealthy and can boast a bona-fide culture of fitness as represented by the extensive recreational infrastructure around the Charles River (with its opportunities for running and rowing) and that it is the venue of the oldest and most prestigious individual athletic event in the country: the Boston Marathon.

To support this assertion, a view of the cities at the bottom of the ranking (Table 4) shows them to be wholly lacking in either economic power or recreational attraction. While they may not be the absolutely poorest cities (Detroit, MI boasts an annual income above the median), they do absolutely lack any measure of amenities that might draw a self-selecting population. It is perhaps for this reason that neither amenity nor income alone is required to select a city as fit but the absence of both will affirmatively exclude it.

Because fit cities exist where (barring the extremes) amenities *and* income intersect, it suggests that fitness behavior is associated with a population where economic power and the personal latitude for self-definition intersect. More precisely it is associated with cities of high status. The fit in America are either living in the political-economic power centers such as Stamford, Bethesda, San Francisco, New York or the outdoor recreation centers such as Montana, Colorado and Hawaii. At the risk of playing upon stereotypes, it can be said that the fit are either the educated elite or their young adult children, eschewing parenthood, scaling rock peaks, working for little income, but living in places where little income is required. Either way it suggests that fitness belongs those who posses sufficient social latitude to materially organize their lives according to their desires. Whether that organization involves commanding a large income and economic influence or an abandonment of responsibility beyond the responsibility for oneself, being fit represents a high degree of choice over how one organizes his/her life.

Choice, Identity and Health Behavior

As the characterization in the previous suggestion suggests, the role of choice and self-identity in determining health outcomes has emerged as a useful paradigm for understanding healthy behavior. Some promising work on identity/social cognitive theory demonstrates the influence of self-identity on the maintenance of health behaviors. One study has shown that the self-identity as a "healthy-eater" is strongly correlated with healthy eating habits or that a strong self-identity as a "runner" is the best predictor of whether an individual will maintain exercise behavior even when confronted with challenges that would hinder his/her ability to run (Strachan 2005). While the Strachan study does not seek to evaluate the prevalence of a fitness identity as somehow indicated by the relative proportion of low-BMI population, identity theory suggests that health and fitness behaviors are internally motivated and better understood as, first, individual behavior, and second, within the context of identity.

Just such a connection is suggested by emerging conceptualizations of health behavior which suggest that personal responsibility for health is entangled with personal identity as it relates to social distinction. First, it can be conceptualized as a postmodern outcome (Cockerham et al. 1997; Glassner 1989). By that it is meant that the individualization of health practice has tracked with the devolution of responsibility from the divine (pre-modern) to science (modern) to the individual (postmodern). For example, whereas modern science dealt effectively with the pre-modern mortal threats of infectious disease it has since found itself confronted with degenerative killers such as heart disease and hypertension that seem beyond its reach. It has thus fallen to the individual to fend off death (Glassner 1989) by maintaining health or wellness through individual effort. It has further been suggested that neo-liberal public institutions have *abandoned* responsibility for public health by actively pushing responsibility away from government and onto the people (Silk and Andrews 2006).

Such devolution to individual responsibility is important to this study for the light it sheds on the more general trend toward individual responsibility for defining oneself within a social structure. Contemporaneous with the individual now facing mortality on his own without God or science, self-identity has emerged as a way to give an individual a means of preserving his autonomy in the face of a fluid social order (Cockerham et al. 1997). The construction of self-identity as a means of social distinction is grounded in Weber's suggestion that social identity is no longer expressed in the modern sense of class stratification (i.e., by way of one's relation to means of production) but rather through one's practices of *consumption.* The notion of social definition through consumption was refined by Bourdieu (1984) to posit *taste* as the differentiating praxis for defining social order. Taste does so by serving as a representation of the "cognitive map" which guides members of social groups in the proper expression of consumption and therefore social group membership (Cockerham et al. 1997). A manifestation of taste in a social construct is, according to Bourdieu, *lifestyle. Lifestyle* is the system of tastes that reflects participation in and definition by social group. Furthermore lifestyles, "function as forms of cultural capital with symbolic values." (Cockerham et al. 1997, 328).

Defining one's body can therefore be understood a social practice and the definition of one's body is therefore a marker of social distinction. In other words, one's lifestyle is reflected in his or her body and his or her body reflects his or her lifestyle. If one's body reflects lifestyle and lifestyle reflects social distinction, then the dominant social groups can define *their* bodies as superior and the very embodiment of class (Cockerham et al. 1997). Reviewing the list of the fittest cities and considering their relative importance with regard to economic and recreational (or *lifestyle*) dominance, this study suggests that those places are symbolic of a fit body. Furthermore that insofar as those places are symbols of status, so too is a fit body. A fit body is the physical embodiment of a dominant cultural lifestyle of outdoor fitness, particularly individual fitness (running, rowing, mountain-climbing, cross-country skiing), as represented by the people who have the social latitude to occupy the places where such activities are the attraction.

While such an idea might give light to the distinction between the seventeen fittest cities and the seventeen fattest, it does little to account for the range of variance of the remaining 131. Of course, factors that define fit thus far (economic power and recreational amenity) are not completely absent the least fit cities. Nor are they to be found exclusively in the cultural coffers of the seventeen fittest. Rather the distinction between those cities suggests something about the population composition of each (and of all the cities in-between) that might simultaneously explain the symbolic cultural dominance of an objectively fit body.

Defining the Self-actualized

Revisiting the milieu in which the idea of "Fit Cities" was first brought to the national consciousness (*Men's Fitness* magazine) helps us understand some of the characteristics of this fit population. Judging by the advertising, the magazine is likely targeted at a young, if not affluent, certainly an "up and coming" professional male demographic. More than just affluent and professional, though, the readership is hyper-focused on self-improvement, longevity, health and status. That the survey consistently rewards (as "fit") Richard Florida's cities with high "coolness" and diversity indices (2002) reflects the juxtaposition of the nexus of economic power (diversity and the ability to attract talent) with the nexus of cultural dominance (a fit body). While this study does not seek to validate the connection between the two lists of cities nor the objective link between the demographic of the magazine and the actual residents of Florida's high diversity, "cool" cities, it will examine the correlation between a self focused, self actualizing population as representative of a dominant social order and the objective fit population in the cities of the United States.

Conceiving social indicator data that would help identify a secular, fit-identified – or, more important—a self-actualizing segment of the population is possible but thorny. Education, income and residential mobility all point at such a population but only as surrogates. Fortunately recent demographic research has described the contours of such a segment using fertility behavior as a marker. As suggested by Philippe Aries (1980), fertility changes are powerful demographic markers for social dynamics. Specifically he points out that the fertility decline of the "modern" period (late 18th through early 20th centuries) was motivated by desire to focus more attention on fewer children and is thus a marker for the elevating status of the child in society. That fertility declines have continued to the point where many adults avoid fertility (and indeed actively terminate it) is a marker for the *diminishing* status of the child in society in favor of the adult's scheme for blossoming as an individual (Aries 1980). It follows, then, that identifying a segment of the population who actively avoids fertility (even to the extent of reflexively terminating fertility) might be congruent with a population segment whose members are driven by "blossoming as an individual."

Such a trend of fertility decline has emerged in northern Europe and Japan while individuals pursue competing *personal* goals such as prolonging education, engaging in self-expressive consumerism, improving one's income etc. This trend, called the second demographic transition (Lesthaege and Neidert 2006; van de Kaa 2002) is distinguished from the "first" demographic transition where high fertility was avoided in order to focus greater opportunity on fewer children. When fertility and nuptuality trends in the U.S. population are decomposed by ethnicity it has been shown that the non-Hispanic white population is undergoing a similar fertility transition (Lesthaege and Neidert 2006).

What is useful to this study about the second demographic transition (SDT) is its correlates with other socially defining behaviors. The SDT is, by definition, a postponement of fertility and is thus strongly associated with the emergence of well-educated women in the professional workplace. Because they have affirmatively rejected family-oriented goals (fertility) in favor of personal goals (education, career, etc.) their fertility behavior can therefore be understood as a marker for a particular lifestyle. For example, they tend to be given to a "post-materialist" political orientation (e.g., they tended very strongly to vote *against* George W. Bush in contrast to non-SDT white voters); they tend to engage in "self-expressive consumerism"; and are strongly non-religious (Lesthaege and Neidert 2006). Importantly, their self and social identity cannot be unbounded. They have eschewed parenthood in order to give themselves the social latitude (time and economic means) to express their tastes (and therefore social distinction) in such a way as to define themselves according to their personal desires. Especially when one considers that this is the cohort who is facing mortality alone, without help from God or medicine, it could even be suggested that their motivation to exercise physical muscle might have deeper existential roots than just a desire to exercise their considerable social muscle.

CHAPTER 5

IDENTIFYING WHO IS FIT IN AMERICA

The literature suggests that ecological correlates between the built urban environment and fitness are limited in their explanatory power. Specifically, they find that education and income are better indicators of a healthy BMI. A review of the 90th percentile fit cities adds another explanatory dimension that is still not very well understood: one of cultural dominance or social latitude, perhaps characterized by a more self-focused population. Better outlining the contours of that dimension is the purpose of the remainder of this study. It can be said that such a dimension is the place where intent and environment intersect; that it is a social milieu insofar as the fit places are metaphorical for the milieu.

Redrawing the conceptual model from Chapter 3 in light of the findings outlined therein, we will de-emphasize the influence of the built environment. Because this study will not examine it sufficiently, cultural factors will also be de-emphasized. It should be stated now that cultural influences (together with social influences that this study examines) offer perhaps some of the best insight into this phenomenon. That the present study de-emphasizes them in its approach reflects a limiting of scope by the researcher rather than a statement of unimportance.

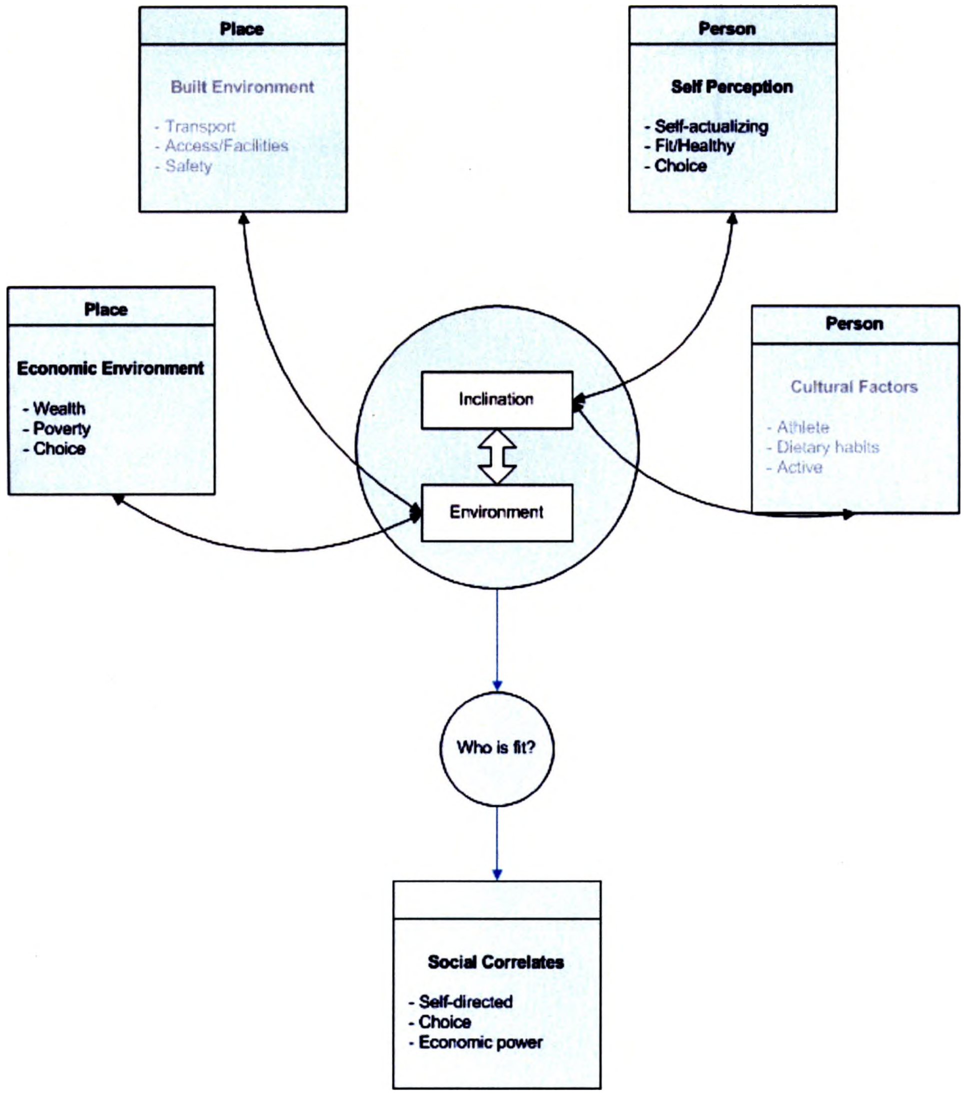


Figure 4. Conceptual Model Reconsidered

As indicated by the findings on identity and health behavior together with the correlates between education, income and a fit BMI, each of those conceptual categories will hereinafter be examined more deeply. Economic factors were considered in the overall "environmental" model and social factors in the "inclination" model (Figure 4). Indeed the insights may be found at the intersection of environment and inclination and may yield a picture of the social factors associated with a self-directed, economically able social group who has the latitude to exercise choice in defining their lifestyle.

Independent Variables

In order to identify such a social group as specified in Figure 4, the self-actualizing population will be operationalized by considering the MMSA-level score on the SDT factor (a Z-score of the SDT characteristics) as defined by Lesthaege and Neidert (2006). The SDT factor was derived by means of a principal components analysis (PCA) in the Lesthaege and Neidert (2006) study and is defined as the factor with high loadings on such variables as postponement indicators of nuptuality (ratio of age at first marriage over age 30 to age at first marriage below age 30) and fertility (ratio of age at first childbirth over age 30 to that below age 30), higher incidence of abortion, higher cohabitation and low overall fertility.

Because previous studies have found significant variation in obesity rates by education and income (Eid et al. 2007, Flegal et al. 2002), this study likewise includes them as independent variables so that their effect can be controlled. In addition, the study includes, as controls against co-linearity between education and a "non-secular" population, the percentage of population (at the county scale) who voted for George Bush in the 2004 election and the percentage identified as "Evangelical" (Table 7). Previous studies also found race to be an important correlate with BMI. Because the SDT is in the United States, by definition, non-Hispanic white, no other variables representing race were considered.

Table 7. Independent Variables

Variable	Description	Source	Scale
SDT Factor	Z-score on SDT characteristics	Lesthaege and Neidert, Population Studies Center, U of Michigan	County
Degreed	Proportion of the population over age 25 with a college degree	US Census Bureau, American Community Survey (ACS) 2006, Table B07009	MMSA
Income per capita	Annual income per capita, 2006 (in chained 2001 dollars)	US Bureau of Economic Analysis, 2005	MSA
Evangelical	Proportion of the population self-reported as Evangelical	Lesthaege and Neidert, Population Studies Center, U of Michigan	County
Bush	Proportion of the population who voted for Bush in 2000	Lesthaege and Neidert, Population Studies Center, U of Michigan	County

A more detailed list of independent variables used in the exploratory data analysis can be found in Appendix A.

Scale Reconciliation

That some data were reported by county while others were reported by MMSA it was necessary to standardize the data on the same spatial scale for the analysis. The OMB definition of MMSA as simply a collection of counties enabled a simple aggregation of county-scale data into their respective MMSAs. All three variables given at the county scale were averaged across the various counties comprising the appropriate MMSA. Dallas-Fort Worth is an example of how counties are aggregated into a single CBSA (Core Based Statistical Area) then re-separated into Metropolitan Divisions. The Dallas-Fort Worth CBSA (FIPS 19100) contains two metropolitan divisions (Dallas-Plano-Irving and Fort Worth-Arlington). Each metropolitan division is simply a collection of counties; Dallas-Plano-Irving with eight and Fort Worth-Arlington with four (Figure 5).

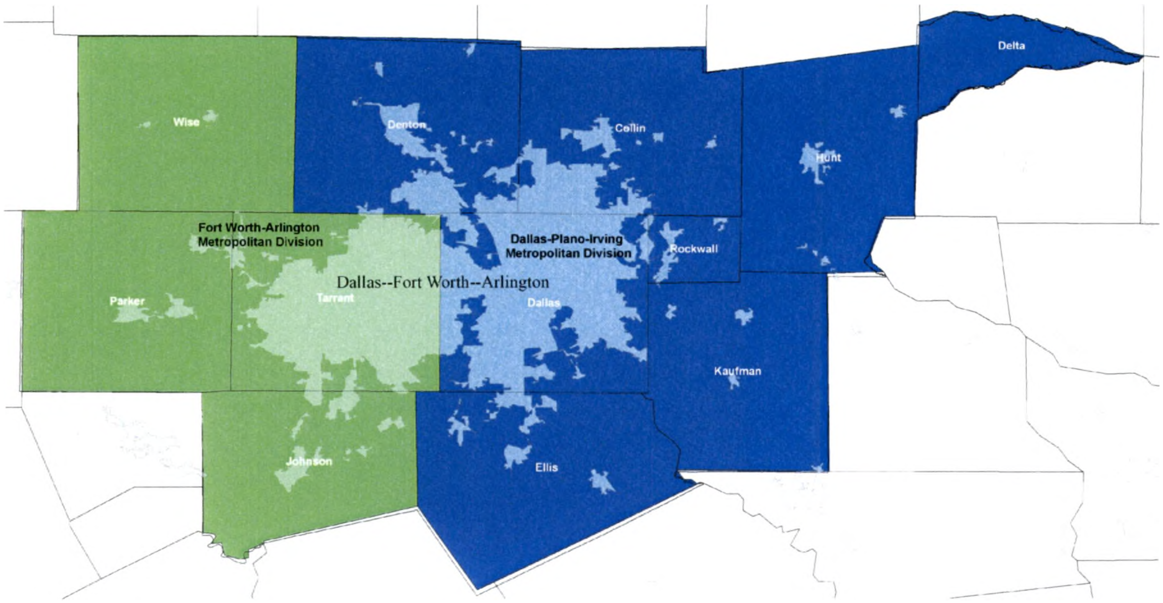


Figure 5. MSA-MSD-County Consolidation

Selection of Indicators

An exploratory analysis of a set of forty-six possible explanatory variables representing Personal (SDT, mobility), Population (age ethnicity etc.) or Ecological (climate, parks, road miles etc.) correlates yielded a reduced set that was used for the remainder of the analysis. (Please see Appendix A for details on the variables.) A Principal Components Analysis (PCA) consolidated the forty-six variables into eleven factors, but the factor loadings did little to distinguish the factors beyond any intrinsic classification in the individual variables themselves. For example, climate factors, age, ethnicity, etc. all grouped into similar factors. It was therefore decided that further analysis could be done with representative variables from the list.

Conceptually, this study focuses on the economic environment and self-identity as the determinants for a fit population (Figure 4). Economic factors are operationalized as per capita income for the year 2006 (BEA). The self-identity factor is operationalized as the SDT factor as described in the section *Independent Variables* above. Interestingly a correlation analysis between some remaining variables showed significant correlations. Percent of the population over the age of 25 with a college degree, percent of the population self-reported as "Evangelical", the percent of the vote for President George Bush in 2004, Daily Vehicle Miles Traveled (DVMT) per capita and parks density all correlated with the fitness rate. The DVMT was significant but with a low beta (unstandardized .86). Because previous studies (Eid et al. 2008; Sööt et al. 2006; Cervero and Duncan 2003) have exposed a nuanced complexity beneath such correlations with ecological factors, it was decided that DVMT per capita and parks density would be left out of further analysis.

Self-actualizing Population and Fitness

In order to explore the hypothesis that a secular, self-actualizing (and low-fertility) class whose presence represents a "fit" city both symbolically and objectively, I conducted a stepwise multivariate regression against the dependent variable of the age-adjusted fitness rate. The assumption of linearity was tested for all independent variables by means of a histogram and bi-variate scatter plots with the age-adjusted fitness rate as the dependent variable.

Table 8. Correlations with fitness rate

	Regression Results				
Independent Variables	**Dependent Variable: age-adjusted fitness rate**				
	Zero-order	Partial	Beta	Cumulative R^2	Tolerance
SDT	.550	.455	.770	.303	.229
% with Degree	.556	.455	.312	.426	.737
Evangelical	-.204	.227	.248	.463	.461
Vote for Bush	-.303	.173	.224	.479	.320

*Note: Variables are listed in the order entered. Missing values were automatically filled with means for each category. All are significant at $\alpha<.05$. N=166.

**Income per capita was not significant at $\alpha<.05$ and was dropped from the model.

Regression results from the final model which considered all five variables show a strong correlation between both SDT and Education against the age adjusted fitness rate (Table 8). Notably, SDT remains as a powerful explanatory variable even when controlled for education and income. The percent of the population self-described as Evangelical together with votes for Bush added little to the overall explanatory power of the model, but served to account for correlates between education and non-SDT populations. What is notable about these results is that SDT *and* Education each had a strong and independent influence on the overall model. While many previous studies have shown a correlation between education and fitness, this study shows, in addition and independently, that SDT helps to characterize the fit population beyond the effect of education level.

It should be noted that per-capita income was entered into the model but did not show a significant correlation and thus dropped out of further analysis. When one considers the variation in income from very low to very high among the fittest cities (Chapter 4) it is unsurprising that income failed to correlate. The better correlates for identifying a self-actualizing population characterized by a high degree of social latitude are education and the fertility postponement behaviors described by the SDT.

The Intermontane West region (AZ, NM, UT, CO, ID, MT and WY) is potentially confounding in our analysis. While it has very high prevalence rates for fitness, it also has a population not very well described by the SDT. Notably, the population composition is predominantly white and Hispanic, religious and politically conservative. Fertility is higher in the region as evidenced by the low median age in the region (approximately two years lower than the rest of the United States). Removing the Intermontane West region from the analysis should therefore have a similar effect to adding statistical controls for religion and political conservatism.

Table 9. Regression model excluding Intermontane West MMSAs

	Regression Results				
Independent Variables	**Dependent Variable: age-adjusted fitness rate**				
	Zero-order	Partial	Standardized Beta	Cumulative R^2	Tolerance
SDT	.601	.466	.448	.357	.772
% with Degree	.535	.353	.321	.433	.772

The results of the analysis show just such an effect to be at work. The variables representing religion and political conservatism dropped out of the analysis as insignificant (Table 9). In addition, the correlation between SDT and fitness was strengthened somewhat and retained its strength even when controlled for education. The high tolerance values for each variable, SDT and percent with a college Degree, in this model indicate a low degree of multi-collinearity between each of the variables. That both variables correlate strongly and are not closely inter-related supports a characterization of fitness as a behavior pattern associated with a self-actualizing, educated population who enjoy a large degree of social self-determination.

It should be noted that both models leave a considerable amount of variance unexplained (cumulative $R^2 = .479$). That is true, of course, because fitness is the exclusive province of neither the highly educated nor the self-actualized. The error in the correlation likely falls both ways: there are some number of self-actualizing, educated people who do not have a fit BMI and there are a (perhaps greater) number of fit people who are so for a variety of reasons beyond their social identity. Therein lies the problem when a fit body is constructed as a status symbol: status might conflict with physiology or with shifts in cultural values over the life course. Such variation could not be accounted for in this study nor was it my purpose. But the association between fitness and an objectively measured social trend is one worthy of further discussion.

CHAPTER 6

DISCUSSION

That an objective measure of fitness (the fit BMI) match the symbolic population with which it is conceptually associated (SDT and educated populations) supports the notion of fitness as both a socially constructed (indeed a socially *defining*) reality that can be represented in space as well as an objectively constructed one. That space does not "make" one healthy cannot be extended to say that there are not healthy places. While one might understand places to be symbolically more healthy than perhaps the objective measures would belie, it is in that social construction of "fitness" that we gain the most insight.

First, we observe that the places where the healthy live are places of high residential preference. That they are attracted by the amenities in places like the Intermontane West, the Pacific Coast or to vibrant cities such as New York and Philadelphia suggests that healthy people make a healthy place and out from their demands of place, their health behaviors are reinforced. Their health outcomes are as much the result of the good fortune—not the good fortune to live in a healthy place, but—to enjoy the social latitude to forge a healthy identity within a place that they can construct both symbolically and objectively as fit. That many of these cities are rewardedby favorable ratings of fitness in the popular press serves to reinforce the understanding of fitness as a status symbol (Silk and Andrews 2006).

Health and Space Redux

Insofar as social structure is often defined in space—for example, by neighborhood (self-)segregation, regional affinity etc.— disentangling the place/person dichotomy has considered the role of individuality in understanding both the symbolic and objective social structure. Despite what the ascendant neoliberal order would have one believe, not all individuals have the same range of choice to define their bodies or their health outcomes. Specifically, it helps to understand that because education and a social context which allows for sufficient latitude to define a healthy lifestyle correlate strongly with fitness, that perhaps choice is the pivot around which fitness is maintained. But it is not rational choices. No reasonable actor would *choose* to be unhealthy, but that some make ostensibly *bad* choices vis-à-vis health behavior might be a reflection of perceived limits on options (Glassner 1989).

Just such an interplay between individual choice and healthy space was ably explored in response to Baltimore's surprise anointing as the "Fittest City in America" by *Men's Fitness* magazine in 2006. Silk and Andrews (2006) examined the mystery behind Baltimore's debut (after having never been ranked in the previous six surveys) and found that the crown was awarded in response to the aggressive campaign of urban renewal being waged by the garrulous, self-promoting Mayor Martin O'Malley. Baltimore was reported to be (symbolically) healthy as demonstrated by the urban renewal of Camden Yards, downtown and the "historic" waterfront. Silk and Andrews point out that much of that urban renewal (including the jogging trails and gymnasiums) has created a space which admits only those who "...fulfill the obligations of participatory democratic citizenship (in this sense, through appropriate rates and acts of fitness consumption)..." and marginalizes (by absolute exclusion) those "...constitutive socially, morally and economically pathologized outsiders (2006, 322)." What is insightful about this spatial boundary-making and its enforcement of social distinction is two-fold. First, that it represents a validation of a neoliberal abdication of public responsibility for the health of its citizens. That by rewarding the slogans, marketing and campaigning by the city of Baltimore to push responsibility for health onto its people, *Men's Fitness* (perhaps unintentionally) reinforces the symbolic construction of fitness as the province of the dominant social order. Second, such a contention is corroborated when one realizes that, in effect, the in-group for whom the new urban spaces are developed is a) a tiny minority and b) the educated, young, affluent, talented people so sought after to "attract" capital investment and the location of creative enterprise as described by Richard Florida (2002).

Healthy space can therefore be also expressed as the objective milieu in which social groups are defined by means of the expressed tastes (consumption) for (among other things) fitness by individuals with the greatest social latitude (economic means). If that is so, then healthy spaces indeed do not encourage fitness in the general population but rather support a lifestyle by serving as extended, publicly-funded playgrounds for affluent adults—perhaps as enticement and reward for attracting the economic interests who seek them as human capital (Silk and Andrews 2006).

In such a light, if there is to be public action for the growing obesity "epidemic" then any public responsibility is not likely to be met by building playgrounds or public campaigns which rely on rational individual choice. Fitness can be understood to exist where intention intersects with a population enabled to define itself. A self-defining population can match its body to its place as is seen in the latitude taken by an affluent population in the amenity-rich places of the Intermontane West to define its body to match its surroundings. Fitness does result from choice and that choice helps define the character of place. But more specifically, if a fit body is a symbolic expression of cultural capital, then one is most likely to find a fit body in the places whose populations are defined by a broader range of choice.

APPENDIX A

VARIABLES

Class	Type	Name	Friendly Name
	Name	N_FIPS_MSA	FIPS (MSA)
	Name	N_FIPS_MSD	FIPS (MSD)
	Name	N_MMSA	MMSA Name
	Name	N_ST	State
	Dependent	D_FIT_PROP	% Fit (2006)
	Dependent	D_OW_PROP	% Overweight (2006)
	Dependent	D_OB_PROP	% Obese (2006)
	Dependent	D_FIT_RATE	Fit Rate (000)
	Dependent	D_FIT_RATE_AA	Age Adjusted Fit Rate (000)
PERS	SDT	SDT_AVG	Average of SDT factor
PERS	SDT	SDT_WEALTH_PROP	Average of Wwealthy (% income > 75,000)
PERS	SDT	SDT_WPROF_PROP	Average of Wprof (Women with professional degrees)
PERS	SDT	SDT_POST_AVG	Average of SDT_Postponement Fctr
PERS	SDT	SDT_COH_AVG	Average of SDT_Cohabitation Factor
PERS	SDT	SDT_EVAN	Percent "Evangelical"
PERS	SDT	SDT_VOTBUSH	Percent vote for Bush
POP	AGE	AGE_MED	Median Age
POP	AGE	AGE_LT18	% Under 18
POP	AGE	AGE_LT25	% Under 25
POP	AGE	AGE_GT70	% Over 70
POP	ETHNICITY	ETH_W	% White
POP	ETHNICITY	ETH_B	% Black
POP	ETHNICITY	ETH_A	% Asian
POP	ETHNICITY	ETH_H	% Hisp
POP	ETHNICITY	ETH_PI	% PI
POP	EDUCATION	ED_LTHS	% LT HS
POP	EDUCATION	ED_DEG	% Degree
POP	EDUCATION	ED_GRAD	% Graduate Degree

Class	Type	Name	Friendly Name
PERS	MOBILITY	MOB_MOVED_PROP	% Moved last year
PERS	MOBILITY	MOB_PROP_DEG_NEW	Of degreed, % new
PERS	MOBILITY	ED_RATIO_NEW_DEG	Ratio New Degreed / Total New
ECOL	CLIMATE	CLIM_SUN	Sunny (% possible sunshine)
ECOL	CLIMATE	CLIM_HUM	Humid (average rel. humidity)
ECOL	CLIMATE	CLIM_RAIN	Rainy (days precip. > .01 in.)
ECOL	CLIMATE	CLIM_WET	Wet (normal annual precip.)
ECOL	CLIMATE	CLIM_COLD	Frigid (# days min temp < 32)
ECOL	CLIMATE	CLIM_HOT	Sweltering (# days max temp > 90)
ECOL	CLIMATE	CLIM_DREARY	Dreary (# cloudy days)
ECOL	ECONOMY	ECON_GDPtoINCOME	Ratio of GDP to Income (2005)
ECOL	ECONOMY	ECON_INCOM_PCAP	Per Capita Personal Income 2005
ECOL	ECONOMY	ECON_GDP_PCAP	Per Capita GDP (2005)
ECOL	ECONOMY	ECON_PROP_HU_OO	% HU owner occupied
ECOL	ECONOMY	ECON_PROP_HU_VAC	% HU vacant
ECOL	ECONOMY	ECON_PROP_HU_NEW	% struc built since 2000
ECOL	COMMUTE	COM_LT15	% < 15
ECOL	COMMUTE	COM_LT30	% < 30
ECOL	COMMUTE	COM_LT60	% < 60
ECOL	COMMUTE	COM_GT60	% > 60
ECOL	ECONOMY	ECON_GINI	GINI index
ECOL	ECONOMY	ECON_POV_PROP	% 1.5x poverty
ECOL	ROADOMY	ROAD_MI_ThPOP	Road Miles/Pop (000)
ECOL	ROAD	ROAD_POP_MI	POP / RD (MI)
ECOL	ROAD	ROAD_DVMT_CAP	DVMT PER CAP
ECOL	PARKS	PARKS_DENSITY	City Pop Density to Park Pop Density
ECOL	AIR	AIR_GOOD_PROP	% Days good AQI

APPENDIX B

COMPLETE LIST OF CITIES RANKED BY AGE-ADJUSTED FITNESS RATE

Age Adjusted Rank	Metropolitan/Micropolitan Area	Age Adjusted Rate (000)	Age Adj Rank Change
1	Santa Fe, NM Metropolitan Statistical Area	491	0
2	Cambridge-Newton-Framingham, MA Metropolitan Division	478	0
3	Bethesda-Gaithersburg-Frederick, MD Metropolitan Division	451	0
4	San Francisco-Oakland-Fremont, CA Metropolitan Statistical Area	443	0
5	Bridgeport-Stamford-Norwalk, CT Metropolitan Statistical Area	443	0
6	Burlington-South Burlington, VT Metropolitan Statistical Area	433	0
7	Colorado Springs, CO Metropolitan Statistical Area	425	3
8	Salt Lake City, UT Metropolitan Statistical Area	423	0
9	Kahului-Wailuku, HI Micropolitan Statistical Area	419	6
10	Hilo, HI Micropolitan Statistical Area	419	2
11	Denver-Aurora, CO Metropolitan Statistical Area	418	3
12	Kalispell, MT Micropolitan Statistical Area	418	5
13	Missoula, MT Metropolitan Statistical Area	417	-4
14	New York-White Plains-Wayne, NY-NJ Metropolitan Division	416	-1
15	Boston-Quincy, MA Metropolitan Division	416	-4
16	Honolulu, HI Metropolitan Statistical Area	410	0
17	Philadelphia, PA Metropolitan Division	410	1

Age Adjusted Rank	Metropolitan/Micropolitan Area	Age Adjusted Rate (000)	Age Adj Rank Change
18	Seattle-Bellevue-Everett, WA Metropolitan Division	408	2
19	Asheville, NC Metropolitan Statistical Area	406	4
20	Portland-South Portland-Biddeford, ME Metropolitan Statistical Area	405	5
21	Medford, OR Metropolitan Statistical Area	405	0
22	Nassau-Suffolk, NY Metropolitan Division	403	2
23	Dallas-Plano-Irving, TX Metropolitan Division	402	-4
24	Provo-Orem, UT Metropolitan Statistical Area	401	-17
25	Cincinnati-Middletown, OH-KY-IN Metropolitan Statistical Area	400	-3
26	Orlando-Kissimmee, FL Metropolitan Statistical Area	395	3
27	Santa Ana-Anaheim-Irvine, CA Metropolitan Division	394	3
28	Newark-Union, NJ-PA Metropolitan Division	394	8
29	Albuquerque, NM Metropolitan Statistical Area	392	4
30	Los Angeles-Long Beach-Glendale, CA Metropolitan Division	392	-2
31	Durham, NC Metropolitan Statistical Area	391	-5
32	Boise City-Nampa, ID Metropolitan Statistical Area	391	-1
33	Phoenix-Mesa-Scottsdale, AZ Metropolitan Statistical Area	390	-1
34	Winston-Salem, NC Metropolitan Statistical Area	390	6
35	Tampa-St. Petersburg-Clearwater, FL Metropolitan Statistical Area	390	6
36	Trenton-Ewing, NJ Metropolitan Statistical Area	389	-2
37	Lebanon, NH-VT Micropolitan Statistical Area	389	2
38	Washington-Arlington-Alexandria, DC-VA-MD-WV Metropolitan Division	387	4
39	Fayetteville-Springdale-Rogers, AR-MO Metropolitan Statistical Area	387	-4
40	Lake Charles, LA Metropolitan Statistical Area	386	-2
41	Edison, NJ Metropolitan Division	386	3
42	Hilton Head Island-Beaufort, SC Micropolitan Statistical Area	386	1

Age Adjusted Rank	Metropolitan/Micropolitan Area	Age Adjusted Rate (000)	Age Adj Rank Change
43	Houston-Sugar Land-Baytown, TX Metropolitan Statistical Area	386	-6
44	Ogden-Clearfield, UT Metropolitan Statistical Area	385	-17
45	Hartford-West Hartford-East Hartford, CT Metropolitan Statistical Area	385	0
46	Essex County, MA Metropolitan Division	383	4
47	St. Louis, MO-IL Metropolitan Statistical Area	383	0
48	Lancaster, PA Metropolitan Statistical Area	381	1
49	Worcester, MA Metropolitan Statistical Area	380	-1
50	Scranton--Wilkes-Barre, PA Metropolitan Statistical Area	379	6
51	Willimantic, CT Micropolitan Statistical Area	378	0
52	Olympia, WA Metropolitan Statistical Area	378	0
53	Manchester-Nashua, NH Metropolitan Statistical Area	377	9
54	Miami-Fort Lauderdale-Miami Beach, FL Metropolitan Statistical Area	377	5
55	Wenatchee, WA Metropolitan Statistical Area	376	2
56	Concord, NH Micropolitan Statistical Area	375	4
57	Greensboro-High Point, NC Metropolitan Statistical Area	374	6
58	Keene, NH Micropolitan Statistical Area	374	-3
59	Atlanta-Sandy Springs-Marietta, GA Metropolitan Statistical Area	373	2
60	Charlotte-Gastonia-Concord, NC-SC Metropolitan Statistical Area	371	5
61	Lincoln, NE Metropolitan Statistical Area	371	-15
62	Coeur d?Alene, ID Metropolitan Statistical Area	371	5
63	Rockingham County-Strafford County, NH Metropolitan Division	371	15
64	Myrtle Beach-Conway-North Myrtle Beach, SC Metropolitan Statistical Area	370	12
65	Portland-Vancouver-Beaverton, OR-WA Metropolitan Statistical Area	370	6
66	Baltimore-Towson, MD Metropolitan Statistical Area	370	2

Age Adjusted Rank	Metropolitan/Micropolitan Area	Age Adjusted Rate (000)	Age Adj Rank Change
67	Austin-Round Rock, TX Metropolitan Statistical Area	370	-14
68	Tucson, AZ Metropolitan Statistical Area	369	-4
69	Des Moines-West Des Moines, IA Metropolitan Statistical Area	369	0
70	Providence-New Bedford-Fall River, RI-MA Metropolitan Statistical Area	369	-4
71	Minneapolis-St. Paul-Bloomington, MN-WI Metropolitan Statistical Area	368	1
72	Baton Rouge, LA Metropolitan Statistical Area	368	-14
73	Indianapolis-Carmel, IN Metropolitan Statistical Area	368	0
74	Chicago-Naperville-Joliet, IL-IN-WI Metropolitan Statistical Area	368	-4
75	Great Falls, MT Metropolitan Statistical Area	366	8
76	Pittsburgh, PA Metropolitan Statistical Area	366	11
77	Atlantic City, NJ Metropolitan Statistical Area	365	3
78	Reno-Sparks, NV Metropolitan Statistical Area	365	6
79	Grand Rapids-Wyoming, MI Metropolitan Statistical Area	365	-4
80	Hickory-Morganton-Lenoir, NC Metropolitan Statistical Area	364	14
81	Greenville, SC Metropolitan Statistical Area	364	0
82	Warren-Troy-Farmington Hills, MI Metropolitan Division	363	13
83	Eugene-Springfield, OR Metropolitan Statistical Area	363	-6
84	Norwich-New London, CT Metropolitan Statistical Area	363	8
85	Wilmington, NC Metropolitan Statistical Area	362	5
86	Camden, NJ Metropolitan Division	362	2
87	Akron, OH Metropolitan Statistical Area	362	-2
88	Ocean City, NJ Metropolitan Statistical Area	362	14
89	Springfield, MA Metropolitan Statistical Area	361	-15
90	Dayton, OH Metropolitan Statistical Area	360	-1
91	Fargo, ND-MN Metropolitan Statistical Area	360	-37
92	Chambersburg, PA Micropolitan Statistical Area	360	5

Age Adjusted Rank	Metropolitan/Micropolitan Area	Age Adjusted Rate (000)	Age Adj Rank Change
93	New Haven-Milford, CT Metropolitan Statistical Area	360	-2
94	Virginia Beach-Norfolk-Newport News, VA-NC Metropolitan Statistical Area	359	-12
95	Bismarck, ND Metropolitan Statistical Area	359	-9
96	Shreveport-Bossier City, LA Metropolitan Statistical Area	358	-3
97	Cleveland-Elyria-Mentor, OH Metropolitan Statistical Area	357	8
98	New Orleans-Metairie-Kenner, LA Metropolitan Statistical Area	356	6
99	Casper, WY Metropolitan Statistical Area	356	-1
100	Milwaukee-Waukesha-West Allis, WI Metropolitan Statistical Area	356	1
101	Lansing-East Lansing, MI Metropolitan Statistical Area	355	-22
102	Idaho Falls, ID Metropolitan Statistical Area	355	-6
103	Columbia, SC Metropolitan Statistical Area	353	-4
104	Kennewick-Richland-Pasco, WA Metropolitan Statistical Area	352	-4
105	Anchorage, AK Metropolitan Statistical Area	350	1
106	Jacksonville, FL Metropolitan Statistical Area	350	5
107	Charleston-North Charleston, SC Metropolitan Statistical Area	350	1
108	Oklahoma City, OK Metropolitan Statistical Area	350	-5
109	Richmond, VA Metropolitan Statistical Area	350	1
110	Rapid City, SD Metropolitan Statistical Area	349	3
111	Clarksville, TN-KY Metropolitan Statistical Area	349	-4
112	Kansas City, MO-KS Metropolitan Statistical Area	349	3
113	Tulsa, OK Metropolitan Statistical Area	348	1
114	Rochester, NY Metropolitan Statistical Area	348	-5
115	Wilmington, DE-MD-NJ Metropolitan Division	344	4
116	Dover, DE Metropolitan Statistical Area	343	0
117	Wichita, KS Metropolitan Statistical Area	343	0
118	Raleigh-Cary, NC Metropolitan Statistical Area	343	2
119	Las Vegas-Paradise, NV Metropolitan Statistical Area	343	8

Age Adjusted Rank	Metropolitan/Micropolitan Area	Age Adjusted Rate (000)	Age Adj Rank Change
120	Buffalo-Cheektowaga-Tonawanda, NY Metropolitan Statistical Area	342	2
121	Cheyenne, WY Metropolitan Statistical Area	342	7
122	Knoxville, TN Metropolitan Statistical Area	341	8
123	Tacoma, WA Metropolitan Division	340	2
124	Flint, MI Metropolitan Statistical Area	340	8
125	Omaha-Council Bluffs, NE-IA Metropolitan Statistical Area	339	1
126	Hagerstown-Martinsburg, MD-WV Metropolitan Statistical Area	338	5
127	Columbus, OH Metropolitan Statistical Area	338	2
128	Birmingham-Hoover, AL Metropolitan Statistical Area	338	8
129	Farmington, NM Metropolitan Statistical Area	337	-8
130	San Diego-Carlsbad-San Marcos, CA Metropolitan Statistical Area	337	-12
131	Memphis, TN-MS-AR Metropolitan Statistical Area	337	4
132	Bremerton-Silverdale, WA Metropolitan Statistical Area	335	7
133	Houma-Bayou Cane-Thibodaux, LA Metropolitan Statistical Area	334	4
134	Spokane, WA Metropolitan Statistical Area	334	0
135	Lubbock, TX Metropolitan Statistical Area	334	-23
136	Riverside-San Bernardino-Ontario, CA Metropolitan Statistical Area	333	-12
137	Fairbanks, AK Metropolitan Statistical Area	331	-14
138	Billings, MT Metropolitan Statistical Area	330	4
139	Sioux Falls, SD Metropolitan Statistical Area	330	1
140	Las Cruces, NM Metropolitan Statistical Area	329	-7
141	Fort Smith, AR-OK Metropolitan Statistical Area	329	0
142	El Paso, TX Metropolitan Statistical Area	326	-4
143	Topeka, KS Metropolitan Statistical Area	326	2
144	Florence, SC Metropolitan Statistical Area	325	3
145	Charleston, WV Metropolitan Statistical Area	324	9

Age Adjusted Rank	Metropolitan/Micropolitan Area	Age Adjusted Rate (000)	Age Adj Rank Change
146	Little Rock-North Little Rock, AR Metropolitan Statistical Area	324	-2
147	Toledo, OH Metropolitan Statistical Area	322	-4
148	Alexandria, LA Metropolitan Statistical Area	321	0
149	Yakima, WA Metropolitan Statistical Area	320	-3
150	Augusta-Richmond County, GA-SC Metropolitan Statistical Area	319	1
151	Detroit-Livonia-Dearborn, MI Metropolitan Division	318	2
152	Louisville, KY-IN Metropolitan Statistical Area	318	3
153	Salem, OR Metropolitan Statistical Area	318	-4
154	Seaford, DE Micropolitan Statistical Area	317	5
155	Monroe, LA Metropolitan Statistical Area	316	-5
156	Jackson, MS Metropolitan Statistical Area	315	-4
157	Allentown-Bethlehem-Easton, PA-NJ Metropolitan Statistical Area	314	-1
158	Youngstown-Warren-Boardman, OH-PA Metropolitan Statistical Area	313	0
159	Lawton, OK Metropolitan Statistical Area	308	-2
160	Fort Worth-Arlington, TX Metropolitan Division	308	0
161	Nashville-Davidson--Murfreesboro, TN Metropolitan Statistical Area	304	2
162	Shawnee, OK Micropolitan Statistical Area	303	-1
163	San Antonio, TX Metropolitan Statistical Area	302	-1
164	Fayetteville, NC Metropolitan Statistical Area	267	1
165	Yuma, AZ Metropolitan Statistical Area	267	-1
166	Huntington-Ashland, WV-KY-OH Metropolitan Statistical Area	222	0

APPENDIX C

CALCULATION OF PARKS DENSITY

The parks density per MMSA is a proportion of proportions: the MMSA population density (people per square mile) over the population-to-park density (1,000 people per square mile of park). The numerator, population density, was calculated using the included figures for population in the ESRI shapefiles (Census 2004) and reported area in square miles (population / CBSA area in sq. mi.). The denominator, was calculated by MMSA as population/1000 (Census 2004) / Park area in sq. mi as calculated from the spatial join.

Park square mileage was assessed by performing a simple spatial join of the CBSA (ESRI 2005a) and Parks (ESRI 2005b) layers using ESRI ArcMap v 9.2. Any park feature falling completely with in a CBSA was "awarded" to the target CBSA. Because a park had to fall *completely* within a CBSA to be awarded, many parks were not counted in the analysis. Such is a limitation of the spatial join capability in ArcMap 9.2. While the layers could have been joined using a different algorithm, any other technique would have double-counted many parks –especially large National Parks whose boundaries include a very small part of a few CBSAs in two or more CBSAs. While proximity to those parks likely does have a strong influence on residential self selection, it was decided to err on the side of a conservative estimate.

APPENDIX D

AGE STANDARDIZATION

The 2006 BRFSS (n = 355,710) data file was cleaned to remove cases where either reported height exceeded 7' 11" or reported weight exceeded 999 lbs (reported when the actual value was unknown or expressed in metric units) leaving a sample of 336,361. The rows (observations) were then cross-tabulated according to age cohorts as shown in Table 10 to arrive at a nationwide fitness rate for each ten year cohort. In order to enable population comparison with Census data that exclude population below the age of 25 (e.g., percent of the population with a college degree), the cohorts below age 29 were split at age 25. Table 10 shows the percentages underweight (BMI < 18.5), fit (18.5 < BMI < 25), overweight (25 < BMI <30) or Obese (30 < BMI) by age cohort.

Table 10. Distribution of BMI Categories (in %) by cohort (BRFSS 2006)

	Underweight	Fit	Overweight	Obese	N
Under 18	2.83	47.83	34.99	14.35	2,118
18 to 24	4.17	53.38	26.27	16.17	14,570
25 to 29	2.53	43.89	31.56	22.02	17,062
30 to 39	1.60	38.96	33.57	25.88	48,310
40 to 49	1.38	35.94	35.77	26.91	64,063
50 to 59	1.16	31.63	37.38	29.83	71,381
60 to 69	1.35	30.27	39.64	28.74	55,855
70 to 79	2.03	35.43	40.31	22.23	40,858
Over 80	3.70	48.36	35.01	12.93	22,144
Total	1.780	36.505	36.310	25.405	
N	5,987	122,787	122,134	85,453	336,361

Because BMI measurements for people under age 18 are not reliable indicators of obesity, the under 18 age cohort was excluded from the analysis at all levels. Age-adjusted rates are therefore the rate for the population over age 18. Care was taken to ensure that other independent variables were specified so as to exclude population under the age of 18.

Age adjustment had two notable effects on the data. First fitness rates dropped for every city in the study area. The exclusion of the cohort under age 18 most likely accounts for some of the drop while the adjustment to include older cohorts likely accounts for the rest. Table 11 lists the top 25 "fit" cities by age adjusted rate and includes columns for the un-adjusted rank and the change in ranking accounted for by age standardization. A negative number in the AA rank change column indicates that the city dropped by that number of places in the rankings after adjusting for the age composition of the population.

Table 11. Top 25 fit cities by raw and age adjusted rates

MMSA Name	Fit/1000	Fit/1000 (AA)	Rank	AA Rank	AA rank change
Santa Fe, NM Metropolitan Statistical Area	510	491	1	1	0
Cambridge-Newton-Framingham, MA Metropolitan Division	505	478	2	2	0
Bethesda-Gaithersburg-Frederick, MD Metropolitan Division	471	451	3	3	0
San Francisco-Oakland-Fremont, CA Metropolitan Statistical Area	465	443	4	4	0
Bridgeport-Stamford-Norwalk, CT Metropolitan Statistical Area	462	443	5	5	0
Burlington-South Burlington, VT Metropolitan Statistical Area	461	433	6	6	0
Colorado Springs, CO Metropolitan Statistical Area	452	425	10	7	3
Salt Lake City, UT Metropolitan Statistical Area	457	423	8	8	0
Kahului-Wailuku, HI Micropolitan Statistical Area	438	419	15	9	6
Hilo, HI Micropolitan Statistical Area	441	419	12	10	2
Denver-Aurora, CO Metropolitan Statistical Area	440	418	14	11	3
Kalispell, MT Micropolitan Statistical Area	435	418	17	12	5

Missoula, MT Metropolitan Statistical Area	454	417	9	13	-4
New York-White Plains-Wayne, NY-NJ Metropolitan Division	440	416	13	14	-1
Boston-Quincy, MA Metropolitan Division	442	416	11	15	-4
Honolulu, HI Metropolitan Statistical Area	437	410	16	16	0
Philadelphia, PA Metropolitan Division	433	410	18	17	1
Seattle-Bellevue-Everett, WA Metropolitan Division	428	408	20	18	2
Asheville, NC Metropolitan Statistical Area	423	406	23	19	4
Portland-South Portland-Biddeford, ME Metropolitan Statistical Area	422	405	25	20	5
Medford, OR Metropolitan Statistical Area	425	405	21	21	0
Nassau-Suffolk, NY Metropolitan Division	422	403	24	22	2
Dallas-Plano-Irving, TX Metropolitan Division	429	402	19	23	-4
Provo-Orem, UT Metropolitan Statistical Area	458	401	7	24	-17
Cincinnati-Middletown, OH-KY-IN Metropolitan Statistical Area	423	400	22	25	-3

It is notable that the first six cities retained their relative ranking even after adjusting for age. Colorado Springs actually climbed a bit in the ranking, Salt Lake City maintained position, and a few cities in Hawaii likewise climbed. Notable, also, are the relatively minor drops for Missoula, MT and Boston-Quincy (but, surprisingly, not Cambridge-Newton-Framingham). The most outstanding drop is that of Provo-Orem UT which dropped from 7th to 24th. Such a drop indicates that the "fitness" of Provo-Orem's population was likely overstated by a high proportion of young people.

The second effect of age standardization is to attenuate the U-shaped curve across age cohorts and to bring the data into something closer to linear order. A rank order plot of BMI across the 166 cities (Figure 6) shows the data to be linear with a bias at the low and high end of the scale caused by the dramatic difference between cities at the top and bottom of the rankings.

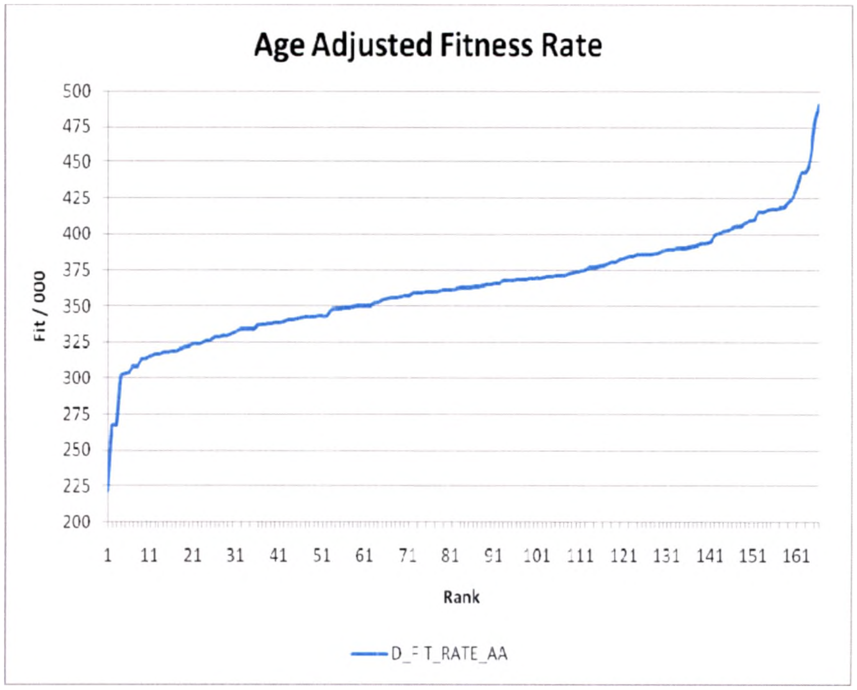


Figure 6. Rank-order Age-adjusted Fitness Rate (n=166)

Removing the three highest and lowest fitness rate values flattens the line considerably as shown in figure 7 and as was discussed in footnote 1.

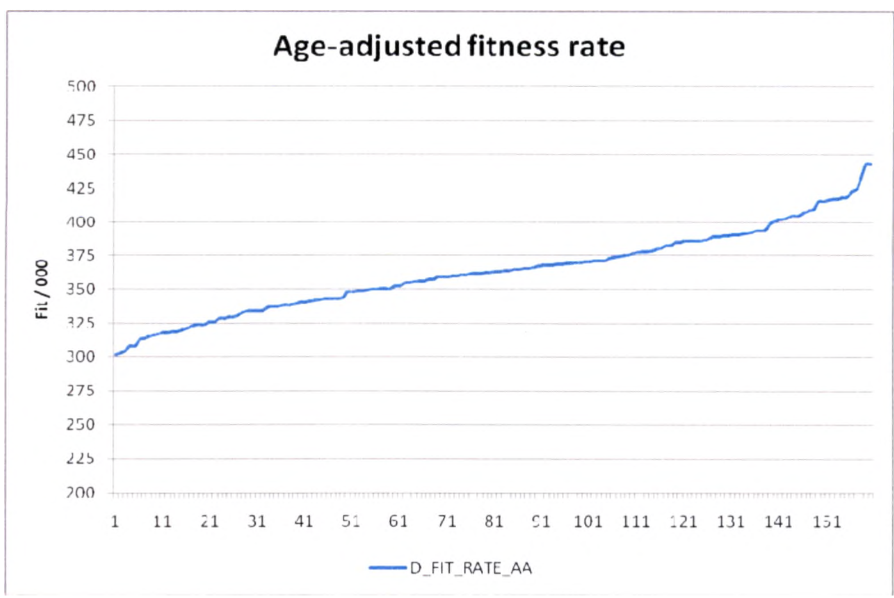
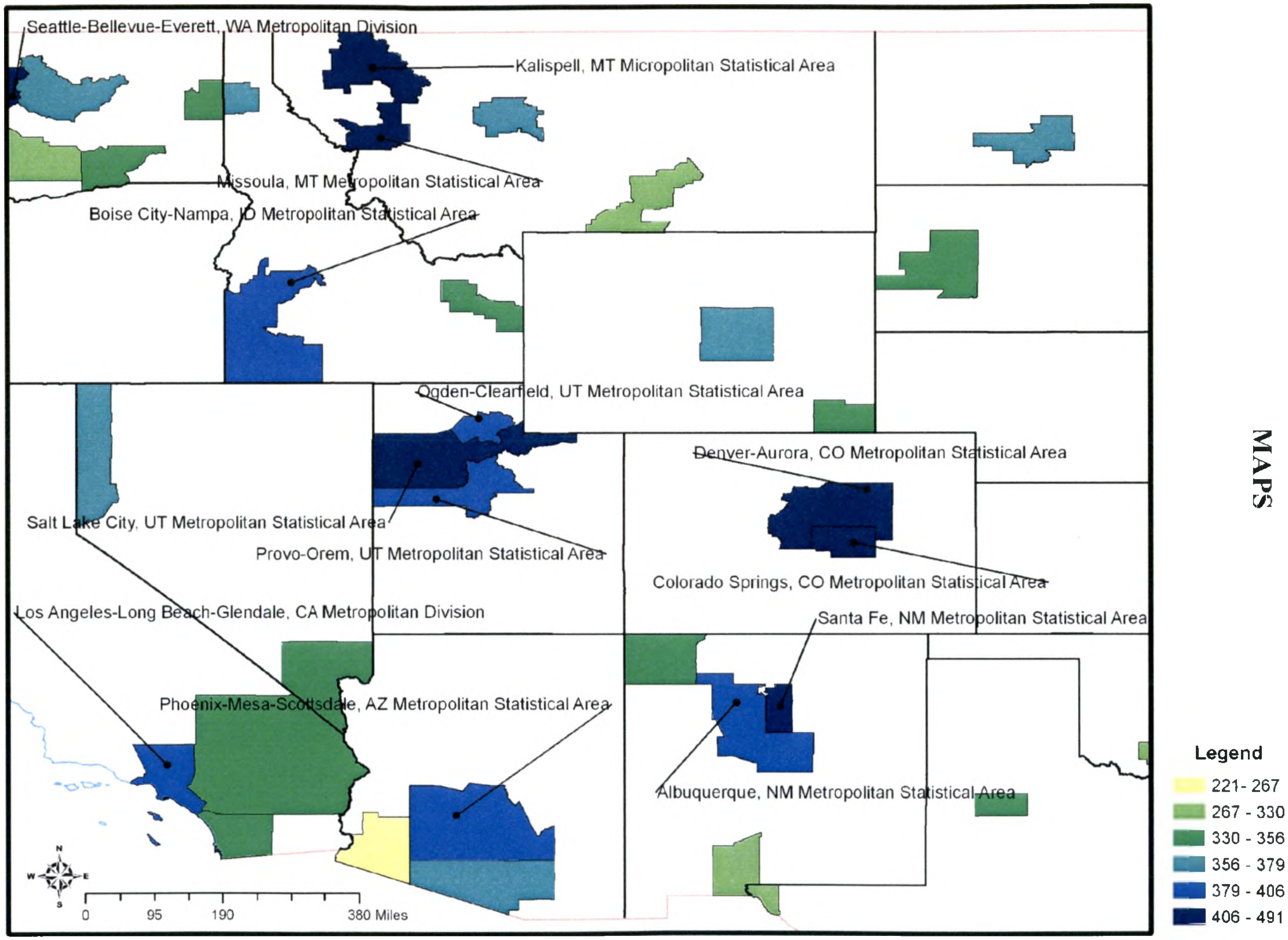
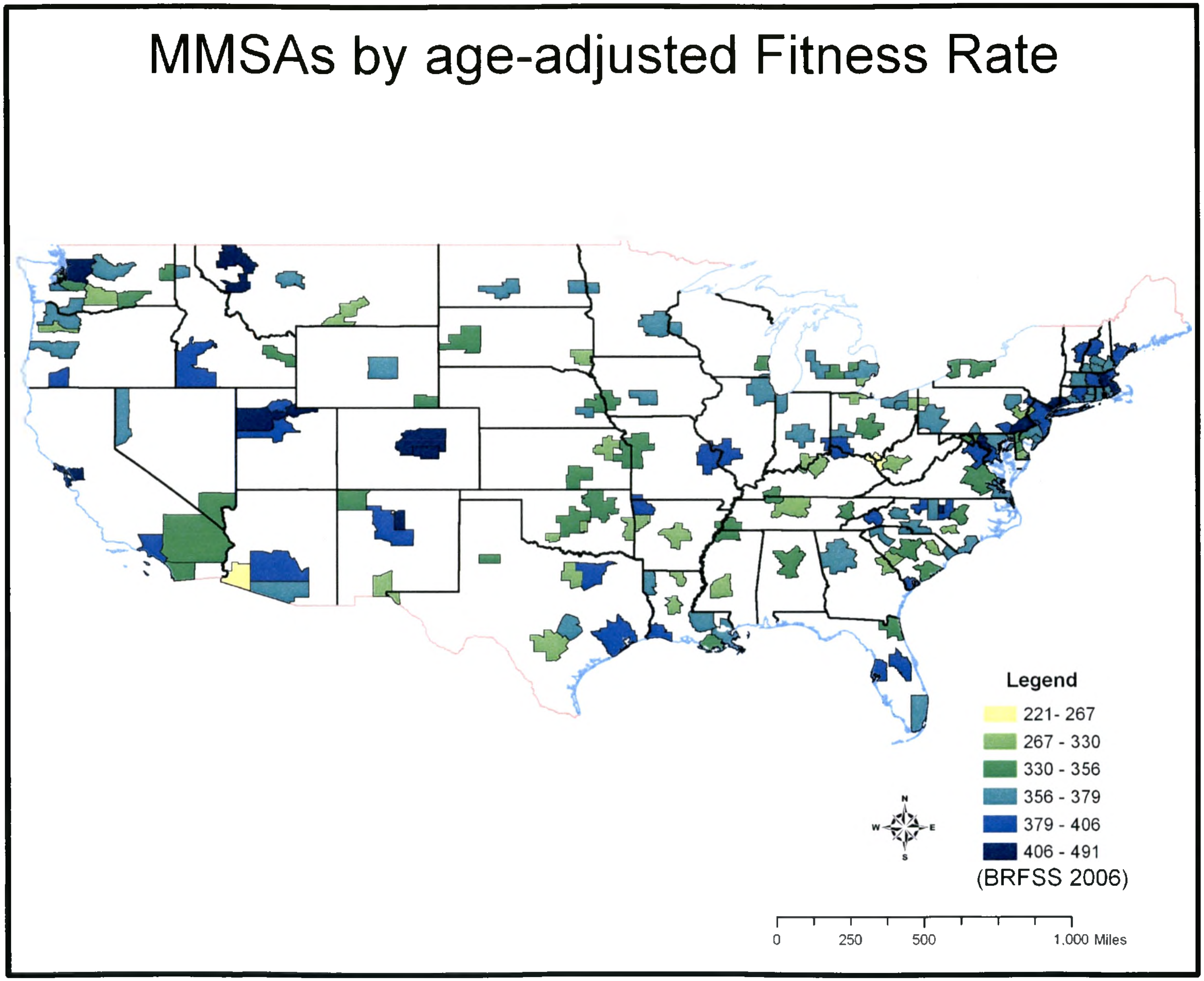


Figure 7. Rank-order Age-adjusted Fitness Rate (n=166)

MMSAs by age-adjusted Fitness Rate



Intermontaine West


MMSAs by age-adjusted Fitness Rate
Legend
221- 267
267 - 330
330 - 356
356 - 379
379 - 406
406 - 491
(BRFSS 2006)
N
W
E
S
0
250
500
1,000 Miles

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