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Title:

A Multifactorial Obesity Model Developed from Nationwide Public Health Exposome Data and Modern Computational Analyses

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Abstract:

Statement of the Problem: Obesity is both multifactorial and multimodal, making it difficult to identify, unravel and distinguish causative and contributing factors. The lack of a clear model of etiology hampers the design and evaluation of interventions to prevent and reduce obesity.

Methods: Using modern graph-theoretical algorithms, we are able to coalesce and analyze thousands of oft inter-dependent variables and interpret their putative relationships to obesity. Our modeling is different from traditional approaches; we make no a priori assumptions about the population, and model instead based on the actual characteristics of a population. Paracliques, noise-resistant collections of highly-correlated variables, are differentially distilled from data taken over counties associated with low versus high obesity rates. Factor analysis is then applied and a model is developed.

Results and Conclusions: Latent variables concentrated around social deprivation, community infrastructure and climate, and especially heat stress were connected to obesity. Infrastructure, environment and community organization differed in counties with low versus high obesity rates. Clear connections of community infrastructure with obesity in our results lead us to conclude that community level interventions are critical. This effort suggests that it might be useful to study and plan interventions around community organization and structure, rather than just the individual, to combat the nation's obesity epidemic.

Key Words:

Obesity Modeling, Graph-Theoretical Algorithms, Factor Analysis

INTRODUCTION

The costs of obesity in the U.S. are staggering — $195 billion annually in ill health and lost worker productivity,[1] with economic impacts of 4.1% of the US Gross Domestic Product ($663 billion). Worse, the prevalence and associated costs of obesity are still growing.[2] By 2030, the direct US healthcare costs of obesity are predicted to be $860-960 billion.[3] Greater than 6.1 million children (2-10 years), 7.7 million adolescents (11-19 years),[4,5] and 72 million adults[6] are overweight/ obese — *one-fourth of the entire U.S. population!*

The obesity epidemic is complex and difficult to address, in large part because the pathway to obesity is multifaceted and factors act at micro-, meso-, exo- and macro-levels. Further complicating the development of effective interventions and policies, obesity factors may be differentially associated across place. Moreover, obesity does not seem to have easily-identifiable causal pathways. Rather, it has many interactions between multi-modal factors (Chronological, Environmental; Country/State, Community; Neighborhood, Individual) that are posited to cause obesity.[7] Identifying each of the factors, however, does not appear to get us any closer to slowing the obesity epidemic. Thus, multi-factorial pathways to obesity create a unique problem when trying to establish public health action points.

Obesity interventions and policies are often designed to focus on a single level, without considering how geography moderates the ways factors can affect obesity. Presently, we are able to describe the rise in obesity rates and the factors that are suspect in obesity development. But studies tend to be contradictory; for every study with one conclusion, we seem to have another concluding just the opposite. There is also a lack of clarity about when and how to intervene in order to reduce overall obesity rates. Current interventions are not even grounded as part of a systematic whole. The situation is made all the more difficult by a lack of agreement on which factors drive obesity and on which obesity model captures all spatial and temporal factors.[8]

Research Problem

Approaches to obesity intervention occur at various levels, from individual to neighborhood to community to state to country. Interventions also occur at different ages, from childhood to adolescence to adult.[9] Obesity interventions tend to be either 1) direct actions to change an individual' s energy balance or 2) indirect actions to modify structures that support direct actions.[9] Nevertheless, there is scant available evidence for the overall effectiveness of any approach to stem the epidemic proportions of obesity developing in a population.[9] It is difficult to perform randomized controlled trials in the real world, and thus, we are left with gaps in our understanding about how to develop a comprehensive obesity intervention. Research does show that many interventions aiming to prevent obesity have the potential to generate additional long-term health benefits by delaying the onset of obesity-related diseases,[10] but the actual efficiency of individual interventions on reducing population obesity is unknown. All proposed obesity interventions have one thing in common: an intervention starting point was not located within a well-defined obesity model.

Modeling with complex network analysis has the potential to develop a multi-modal, multi-factorial model grounded in space and time for obesity that can be used as the base to inform and address the obesity epidemic. We have modeled the development of obesity in the geographic United States from 2000 to 2010. We used our public health exposome database for the modeling (explained in the sequel).[11] Our approach innovates obesity modeling by building on previous applications of complex network analysis using county-level data focusing on pre-term birth,[12] black male premature mortality and lung cancer mortality.[13] By contrasting counties with relatively low rates of obesity with those with relatively high rates, we begin the complex process of determining which factors contribute to the epidemic and which may potentially be malleable to intervention.[14-16]

METHODS

Background

The exposome has been proposed as an alternative way to look at the cumulative effects of exposures throughout the life course, including those that can cause poor health outcomes such as obesity. Many different types of exposure may have effects on the development of obesity. While behavior and genetics are known to play a role, we are just beginning to explore effects due to exposure. A main goal of this work is to use the exposome to identify and unravel shared mechanisms and common biological pathways underlying obesity development, which then have direct implications for the development of targeted individual and community obesity interventions.[11] An exposome approach combines exposure science and social-ecological models in order to provide insights into the underlying causal mechanisms through which environmental exposures affect individual obesity that may then lead to population-level obesity. Traditional exposure science models typically examine the impact of the environment on disease through a narrow reductionist approach, supported by discipline-driven theories that lead to focused assessments, models, and analytics. Our approach is different.[11] We conceptualize the cumulative effects of exposures across the lifecycle (from conception to death) to examine dynamic, multi-dimensional inter-relationships between all levels of the environment with obesity development.[11] Thus, environmental dependency can be explored as a pathway to obesity. Past exposome science has been rather limited, because it has focused largely on the effects of endogenous exposures such as a specific chemical pollutant on a specific disease, sub-populations, time period or geographic region. We have expanded the exposome concept further to include endogenous and exogenous exposure mechanisms, processes and outcomes with mediating and moderating factors at both the individual and population health levels (i.e. factors such as: 1) weather/ climate, 2) environmental pollutants-air and water borne, 3) sociocultural by race and ethnicity, deprivation-segregation/ isolation, risk behaviors- purchasing patterns/ seeking healthcare, community health-diabetes/ infant mortality/ disability/ healthcare infrastructure, 4) policy -food access/ government program participation and economic factors-housing stock/ education/ marital status/ income/ occupation). These we call the Public Health exposome.[11] The Exposome provides more insight into health outcomes. "…the distinction between people and places, composition and context, is somewhat artificial. People create places, and places create people"[17] to understand health risks, individuals need to be placed both spatially in a geographic location and also temporally by their age; only then can we begin to look at all the factors that create specific health outcomes.

Our data contains approximately 12,000 public health variables that have been geocoded spanning the years 1990 to 2010. These variables can be grouped into five broad categories: social indicators (descriptors of social/economic conditions such as poverty, crime, demographic characteristics, racial segregation and unemployment found in an area or population); built factors (attributes of places we live, work, play, learn and pray, with measures of both quality, quantity and access), natural environment measures (exposure measures of air, climate, water, land and pollutants), health factors (mortality, morbidity, screening, behaviors and disease specific indicators), and policy items (governmental laws, ordinances, regulations and programs that have either a direct or indirect impact on health). These variables are stored in a database that allows for rapid extraction and query. Database structure allows for storage in arbitrary format, which eliminates the need for extensive data cleaning and manipulation prior to analysis.[18]

Before proceeding, we briefly outline our approach. We first split exposome data into quintiles using the adult obesity rate from 2009. Next, we separate the highest and lowest quintiles for differential graph-theoretical analysis[13]. Using results of this analysis, we then identify latent constructs by factor analysis use these constructs to study hidden networks and relationships in the data.

Computational Analysis

In order to identify and amass variable subsets possessing quantifiable measures of similarity, we extracted two sets of paracliques,[19,20] one from counties in the highest 2009 obesity quintile (n= 781), the other from the lowest 2009 profile (n= 797). Paracliques were computed as follows. A symmetric correlation matrix was first created, whose entries represented correlation coefficients between variables. From this matrix a weighted correlation graph was built, in which vertices represented variables and edges were annotated with coefficients. Spectral methods[21] were next applied to compute thresholds, resulting in cutoffs of 0.62 for counties where obesity rates are high, and 0.61 for counties where they are low. We then extracted paracliques for each set of counties, and analyzed correlations to adult obesity that were at least 0.30.[22]
With data dimensionality thereby greatly reduced, exploratory factor analysis became feasible. In order to create latent constructs that measured structural concepts related to obesity, we used factor analysis for two purposes. Initially, factor analysis with an orthogonal rotation was used as a data reduction technique and to explore the relationships between variables and the underlying concept associated with each paraclique. These initial factor analyses determined the factor loadings and the direction of the loadings for each variable within each paraclique. Graph Analysis was used to connect the paracliques in Figures 1 and 2. Paracliques are developed which have pairs of its vertices composed of densely packed variables connected by an edge. There is no directionality between the paracliques, just evidence the paracliques are connected. High and low construct structures before inclusion post-processing are depicted in Figures 1 and 2, respectively.
Based on these analyses, we created a conceptually purer set of latent constructs by including only variables with a relatively high factor loading (an absolute value 0.45). Varimax rotation was used, and factor solutions were determined for each paraclique, some of which yielded single variable constructs while others produced multivariable constructs. Paracliques were thus used to isolate latent constructs, iterating until all factor loadings were at least 0.45 in the principal components matrix, where 0.45 was chosen to maximize cogency and reduce noise in the constructs.[23,24] This facilitated the creation of latent constructs that hone in specifically on each structural concept, and allows for the calculation of reliability scores for each latent construct. We then re-applied spectral methods, this time to set construct graph inclusion limits, which were 0.43 in the high

obesity counties and 0.29 in the low. Variables correlated to and factoring with obesity were used to develop multi-factorial models of obesity contributors. Correlation coefficients between the latent constructs was used to connect the latent constructs in Figures 3 and 4; the positive and negative associations between the latent constructs provide directionality (i.e. positive or negative). Figures 3 and 4 show these 'purer' structures after inclusion criteria were applied. We discuss these relationships in the next section.

RESULTS

This study provides a county-level analysis of social and environmental predictors of obesity, in 3106 U.S. counties of greater than 100,000 persons, using an exposome database of routinely collected public health variables (public health exposome dataset) and novel computational analyses. County obesity percentages in 2009 ranged from 11.7% in Routt County, CO, to 43.7% in Greene County, AL.

High Obesity Counties **Table 1** lists variables contained in 22 paracliques extracted from high obesity county data. The high obesity county paracliques (i.e. in **Table 1**) are distributed by their connections into four groups as shown in **Figure 1**: (1) Healthcare Infrastructure, Providers, and Crime, (2) White Affluence and Education, (3) Poverty, Disability Climate, Pollution and Minority Population Interaction, and (4) Pollution and Population. There are also 5 unattached paracliques.

Table 3 elucidates the connections between the variables by splitting constructs into separate positive and negative latent constructs (i.e. all variables in a construct either are positively or negatively associated with obesity). The variables are distributed into 21 latent constructs for high obesity counties. Associations between the latent constructs in **Table 3** are shown as lines (*Either positive or negative associations to each other; there is no directionality, rather there are positive and negative associations emanating from correlations.*) in **Figure 3** for the high obesity counties. Twenty (20) of the latent constructs are connected to each other. Some of the constructs have numerous connections to the other constructs: White Income, Education & Occupational Attainment (15); Distance to the Grocery Stores (11); Median Household Income (11); Disability (10). There is large connectedness of the constructs with each other and with obesity, only one construct was not connected to any other construct.

Low Obesity Counties The low obesity counties are different, **Table 2** shows the variables in the 17 paracliques for the low counties. The low county paracliques (i.e. in **Table 2**) are distributed by their connections into 5 groups as shown in **Figure 2**: 1) Healthcare Infrastructure- Hospitals, 2) White Affluence

Education, Family Structure, Disability and Food Insecurity, 3) White Marriage and Housing Stock and Politics 4) Climate and Pollution and 5) Age, Aging and Aging Infrastructure. There are also 21 unattached paracliques.

Table 4 elucidates the connections between the variables in the low counties by again splitting the constructs into separate positive and negative latent constructs (i.e. all variables in a construct either are positively or negatively associated with obesity). The variables are distributed into 23 latent constructs for the low obesity counties. Associations between the latent constructs in **Table 4** are shown as lines (*Either positive or negative associations to each other; there is no directionality, rather there are positive and negative associations emanating from correlations.*) in **Figure 4** for the high obesity counties. Twenty-one (21) of the latent constructs are connected to each other and 2 are connected to no other construct (**Figure 4**). Some of the constructs have numerous connections to the other constructs: Inequity, Food Access & diabetes (13); Black Population, Segregation, Poor Birth outcomes; Life Expectancy (11); Depravation (11); Low White education & high disability (10).

Differences between high and low counties. High counties showed more connectedness between segregation and population race variables with obesity. In the high counties government policies such as food and healthcare programs were centrally placed between the latent constructs. Whereas in the low counties, there was more connectedness between the majority population's indicators of poverty (income, education, marital status, disability) with obesity. Income and distance to grocery stores were centrally placed between the latent constructs.

DISCUSSION

Traditional models typically have examined the impact of factors on obesity through *"a reductionist approach, supported by discipline-driven theories that have led to narrowly focused assessments, models, and analytics".*[11] Relational data is a common form of data in the social sciences, where relationships among factors represent the central object of inquiry. The data can be represented as a network, or mathematical graph, with a set of nodes and another set of edges. Graph theoretically, it then becomes possible to represent a network and measure the density of the nodes. Our study developed an expositional approach supported by big data interpreted through the viewpoints from a transdisciplinary team. Our work expands the calls for social network and system dynamic modeling to include as many factors as possible that may potentially explain the complex connection between obesity and the environment. Many system dynamic models are based on the contagion theory where social influence creates a desired weight that is then passed through a population.[25] Our modeling is different because we make no a priori assumptions about the population and we model based on the actual characteristics of a population.[13] It may not be immediately clear what kinds of network properties are relevant; in fact, that might be precisely the question in which we are interested in the first place. For many factor relationships, theory may suggest that current statistical models do not look beyond more than one or two connections of neighboring factors, so adequately modelling statistics such as the graph analysis might be expected to better show higher-order connections correctly.[26] We stress that nodal covariate information is vital to any attempt at modelling complex multifactorial diseases, and the particular covariates of importance will not be the same for all situations.

Our modeling augments agent based modeling because we can pinpoint the social factors most tightly connected to obesity in populations. Agent based modeling has found that social norms create an environment that either selects or deselects for the development of obesity.[25] This is similar to what we have found that majority population (white) affluence and high educational attainment is tightly and negatively connected to obesity, while conversely, an environment of predominantly blue collar workers or with high levels of poverty appear obesegenic. In counties where obesity is higher, a lack of resources—poverty couples with segregation, poor birth outcomes and disability connect to obesity. In counties where obesity is relatively low, majority population income, disability and access to healthy foods are connected with obesity. Although these results replicate previous findings in agent based modeling, our approach shows that known variables associated of obesity combine in different ways when comparing both types of counties. Also, the strength of these previously documented variables sometimes vary in their association with obesity. Social network analysis has shown that interaction opportunities change distributions of various factors in a system of people.[27] Thus obesity development may change depending upon the interaction opportunities in the high versus low counties. Social depravation and low SES may have more of an effect on obesity development in counties where obesity rates are low, creating pockets of poverty and obesity in a relatively affluent normal weight population. In counties with high obesity rates, there may be systemic poverty, segregation, social depravation so the effects of each individual factor on obesity development is lessened and the structural supports such as government programs may have more impact on driving obesity development. Our model points to structure of the counties changing the distribution of factors related to obesity; some factors are more densely interacting with other factors in low versus high obesity counties.

The connection between obesity and climate and heat stress in humans has not been widely reported.[28] The cause-and-effect chain from climate change to changing patterns of human health and phenotypes is extremely complex and multifactorial (socioeconomic status, public health infrastructure, access to medical care, nutrition, types of agricultural crops produced, safe water, and sanitation).[29] Epigenetics (phenotype selection) is mediated through environmental exposures raising the possibilities of reciprocal feedbacks loops between the climate and human health outcomes caused by phenotype expression. We found a link between obesity and climate temperature, especially heat stress. In both high and low obesity counties an association between climate and pollution with obesity was observed. When looking at low obesity counties, climatic conditions and particulate matter pollution are unconnected with the web of variables tapping differing types of social disadvantage. In high obesity counties these factors are integrated into social disadvantage. Climate, temperature, heat stress derived from the paracliques differ when comparing low and high obesity counties. The climate variables are split between two paracliques in the low obesity counties and pollution variables are intermixed within climate paracliques. Climate and pollution tend to be distinct within the high obesity counties. In high obesity counties contains variables indicating particulate matter pollution, adverse birth outcomes, food insecurity and measures of socio-economic deprivation are all inter-related with the climate and connect to obesity.

Future Directions

Obesity modeling is the equivalent of the 18th-century maps used by epidemiologist, John Snow to understand and address the cholera epidemic.[30] On those maps, there was error between maps and the cholera data they represent, but, "*…The map was not a stand-alone analytic tool but one summarizing (and locating) a wealth of data...*"[30] Our purpose has been to apply state-of-the-art computational tools to generate hypotheses that can model the multi-factorial components of obesity. We suggest where it might be useful to study and plan interventions, but also to identify relationships that might be places to begin to unravel obesity etiology. Our obesity modeling is a starting point to be built upon as we and others compile more comprehensive evidence base for appropriate policies, interventions and resource allocation to reduce the obesity epidemic. We are currently funded to expand the modeling from the population to the individual level. Multi-level modeling will expand the prediction of disease risk and better pinpoint points for intervention that can leverage into better health outcomes.

Limitations

Our methodology allowed a relatively hypothesis-free approach to the investigation of county variation in obesity rates, but the method was not completely hypothesis free, because prior assumptions influenced the choice of variables that were included in the public health exposome dataset. A wide variety of variables was provided but the variables were limited to publicly available data and included a large amount of health service and census data variables. In addition, only a decade (2000-2009) was included in the current analysis; expansion of the time frame of variables would provide a more complete model of obesity etiology.

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Table

Table 1. High Obesity Paracliques that represent County Relationships

Original Paraclique	Paraclique Clusters	Variables	Zero-order correlation with obesity	P-value	Factor loading on latent construct
PHYSICIAN PROVIDERS	**Healthcare Infrastructure, Providers, and Crime**	**RATE_ACTMDS_FEDNONFED**	**-0.263**	<0.001	0.984
		RATE_ACTMDS_NONFED	**-0.262**	<0.001	0.985
		RATE_ANEST_TOT_PC	**-0.263**	<0.001	0.891
		RATE_CARDIO_TOT_PC	-0.161	<0.001	0.895
		RATE_MDS_PC_OFFBASED	**-0.29**	<0.001	0.959
		RATE_MDS_SPEC_TOT_PC	**-0.218**	<0.001	0.963
		RATE_MDS_TOT_PTCARE_NONFED	**-0.266**	<0.001	0.988
		RATE_MDS_TOT_SPEC_OFFBASED	**-0.255**	<0.001	0.948
		RATE_NEURO_TOT_PC	-0.163	<0.001	0.845
		RATE_OPTH_TOT_PC	**-0.234**	<0.001	0.846
		RATE_RADONC_TOT_PC	-0.157	<0.001	0.737
		RATE_SURG_SPEC_TOT_PC	**-0.227**	<0.001	0.95
PHYSICIAN SPECIALITY PROVIDERS		RATE_INTMED_SPEC_TOT_PC	-0.181	<0.001	0.985
		RATE_NEURSURG_TOT_PC	-0.128	<0.001	0.882
		RATE_PLASTIC_TOT_PC	**-0.210**	<0.001	0.857
Hospital Capacity/ Nursing Home		RATE_COMM_HOSP_BEDS	-0.009	0.625	0.901
		RATE_LICENS_NH_HOSP_BEDS	-0.031	0.081	0.914
		RATE_LICENS_SHRTRM_HOSP_BEDS	-0.011	0.522	0.902
		RATE_LICENS_SHRTRM_NH_HOSP_BEDS	-0.028	0.120	0.924
		RATE_SHRTTERM_HOSP_BEDS	-0.006	0.736	0.902
		RATE_SHRTTERM_NH_HOSP_BEDS	-0.026	0.141	0.931

		RATE_TOTAL_INPT_BEDS	0.002	0.897	0.877
		RATE_TOT_NH_HOSP_BEDS	-0.030	0.094	0.921
CRIME		Grndtot_rate	0.004	0.851	0.873
		p1prpty_rate	-0.066	0.006	0.961
		p1tot_rate	-0.033	0.165	0.964
HOSPITAL CAPACITY AND ADMISSIONS		RATE_COMM_HOSP_ADM	0.003	0.854	0.972
		RATE_HOSP_ADMISSION	0.007	0.678	0.971
		RATE_MED_SRG_ADULT_BEDS	0.046	0.011	0.77
		RATE_OP_ROOMS	-0.129	0.103	0.892
		RATE_SHRTTERM_HOSP_ADM	0.008	0.65	0.973
WHITE INCOME	**White Affluence and Education**	**Income_Less_Pov_W**	**0.273**	<0.001	-0.863
		Median_House_Inc_W	**-0.378**	<0.001	0.93
		Per_Cap_Inc_W	**-0.456**	<0.001	0.856
		SNAP_W	**0.348**	<0.001	-0.744
		mhhinwt	**-0.34**	<0.001	0.91
		povwt	**0.247**	<0.001	-0.847
LOW WHITE EDUCATION AND HIGH DISABILITY		**Educ_Less_HS_F_W**	**0.476**	<0.001	0.871
		Health_Status	**0.479**	<0.001	0.843
		Laborforce16_64_BF	**-0.283**	<0.001	-0.818
		Laborforce16_64_WF	**-0.283**	<0.001	-0.818
		PERCNT_MEDCR_ENROL_DISABL_HI	**0.436**	<0.001	0.937
		PERCNT_MEDCR_ENROL_DISABL_SMI	**0.442**	<0.001	0.942
		PERCNT_MEDCR_ENROL_DISABL_TOT	**0.436**	<0.001	0.937
		edlowwt	**0.5**	<0.001	0.877

URBANICITY AND POLLUTION	**Pollution and Population**	Nitrous_Oxide_NEI_Sum_LBSQM	**-0.21**	<0.001	0.923
		Population_Density	-0.13	<0.001	0.874
		uc1	-0.124	<0.001	0.759
POPULATION SIZE		**POP**	**-0.225**	<0.001	0.944
		TOTPOP_2005	-0.194	<0.001	0.988
QUALITY OF LIFE FROM BIRTH	**Poverty, Disability Climate, Pollution and Minority Population Interaction**	**ALE**	**-0.61**	<0.001	-0.846
		PERCNT_MEDCD_ELIG_MALES	**0.445**	<0.001	0.834
		PERCNT_MEDCR_MEDCD_DUAL_ELIG	**0.435**	<0.001	0.817
		Under_18	**0.403**	<0.001	0.854
		f_divorce	**0.41**	<0.001	0.81
MAJORITY POPULATION, POLITICAL ENGAGEMENT & BIRTHS TO UNMARRIED WOMEN		Av_Per_Dem	-0.006	0.753	-0.228
		Av_Per_Rep	0.017	0.336	0.213
		PERCNT_WHITE_POPULATION	**-0.349**	<0.001	0.919
		Per_Dem_04	0.049	0.006	-0.246
		Per_Dem_08	-0.055	0.002	-0.202
		Per_Rep_04	-0.035	0.053	0.24
		Per_Rep_08	0.064	<0.001	0.181
		Unmarried	**0.443**	<0.001	-0.919
HIGH PERCENT BLACK POPULATION, SEGREGATION, WITH POOR BIRTH OUTCOMES		**Iblack2000**	**0.387**	<0.001	0.882
		Iwhite2000	**-0.208**	<0.001	-0.791
		LBW	**0.368**	<0.001	0.837
		PCT_NHBLACK08	**0.468**	<0.001	0.927
		PERCNT_AFRICAN_AM_POP	**0.464**	<0.001	0.928
		Per_Low_Literacy	**0.287**	<0.001	0.706
		Premature	**0.457**	<0.001	0.794
		f_2575	-0.16	<0.001	-0.731

INEQUALITY, FOOD ACCESS & DIABETES		GINI2000	0.19	<0.001	0.761
		PCT_DIABETES_ADULTS	**0.739**	<0.001	0.833
		PCT_HHNV1MI	**0.467**	<0.001	0.85
POVERTY, PUBLIC ASSISTANCE & INCOME		**MED_HH_INC**	**-0.459**	<0.001	-0.806
		PCT_FREE_LUNCH08	**0.495**	<0.001	0.787
		PCT_POV_LT18	**0.464**	<0.001	0.856
		PERCHLDPOV	**0.361**	<0.001	0.491
		PERCNT_FOODSTAMP_RECIPNTS	**0.522**	<0.001	0.819
		PERCNT_MEDCD_ELIG_FEMALES	**0.458**	<0.001	0.876
		PERCNT_MEDCD_ELIG_TOT	**0.461**	<0.001	0.871
		PERSIST_POVERTY	**0.361**	<0.001	0.292
		POV_RATE	**0.477**	<0.001	0.825
FOOD PRICES		MILK_PRICE	0.022	0.218	0.977
		MILK_SODA	0.142	<0.001	0.906
		PC_FATS	-0.02	0.273	-0.823
FOOD HABITS & COST – Fruit/ Vegetables/ Processed Snacks		PC_SNACKS	-0.102	<0.001	0.917
		PC_PREPFOOD	-0.092	<0.001	0.95
		PC_FRUVEG	**-0.21**	<0.001	0.832
CLIMATE		**AvgDailyMaxHeatIndexF**	**0.49**	<0.001	0.864
		DAYS_HI_100	**0.269**	<0.001	0.847
		DAYS_HI_90	**0.331**	<0.001	0.961
		DM_Heat	**0.461**	<0.001	0.834
		DM_Temp	**0.267**	<0.001	0.968
		Temp_min	**0.399**	<0.001	0.933
		land_surf_night	**0.377**	<0.001	0.882

		sunlight	-0.071	<0.001	0.717
HEAT, POLLUTION & PRECIPITATION		**NOR_FPM_H_2**	**0.537**	<0.001	0.943
		Pollution_Heat_Index	**0.553**	<0.001	0.949
		precip	**0.369**	<0.001	0.791
PHYSICIAN INTERNAL MED & SPECIALTIES PROVIDER AGE		percent_gen_intmed_45_64yr	-0.044	0.036	0.934
		percent_gen_intmed_under_45yr	0.052	0.014	-0.934
		percent_med_spec_45_64yr	-0.064	0.002	0.935
		percent_med_spec_under_45yr	0.095	<0.001	-0.933
PHYSICIAN FAM MED & GPS		percent_fam_med_45_64yr	-0.016	0.402	-0.936
		percent_fam_med_under_45yr	-0.047	0.013	0.943
		percent_tot_gps_45_64yr	-0.037	0.045	-0.914
		percent_tot_gps_under_45yr	-0.073	<0.001	0.926
PHYSICIANS RATE FAM MED & GP		rate_mds_fm_tot_pc	-0.173	<0.001	0.981
		rate_mds_gp_tot_pc	-0.156	<0.001	0.982
		rate_mds_tot_fm_offbased	-0.172	<0.001	0.982
		rate_mds_tot_gp_offbased	-0.155	<0.001	0.981
PHYSICIANS DO		rate_actv_do_fednonfed	-0.062	0.001	0.987
		rate_actv_do_nonfed	**-0.262**	<0.001	0.988
		rate_do_tot_ptcare	-0.062	0.001	0.948
WHITE EDUCATION AND OCCUPATINAL ATTAINMENT		**BC_W**	**0.388**	<0.001	-0.914
		BC_WM	**0.404**	<0.001	-0.931
		Educ_Col_F_W	**-0.484**	<0.001	0.935
		Educ_Col_M_W	**-0.489**	<0.001	0.961
		edhighwt	**-0.494**	<0.001	0.955

Table 2. Low Obesity Paracliques that represent County Relationships

Original Paraclique	Paraclique Clusters	Variables	Zero-order correlation with obesity	P-value	Factor loading on latent construct
AGE STRUCTURE+ MEDICARE DISABILITY	**Age, Aging and Aging Infrastructure**	Age_65_84	-0.056	0.002	0.939
		MEDIAN_AGE	-0.154	<0.001	0.925
		MEDIAN_AGE_FEMALE	-0.118	<0.001	0.937
		MEDIAN_AGE_MALE	-0.193	<0.001	0.888
		MEDIAN_AGE_WHITE_NON_HISPANIC	-0.046	0.011	0.838
		MEDIAN_AGE_WHITE_NON_HISP_FMLE	-0.006	0.749	0.832
		MEDIAN_AGE_WHITE_NON_HISP_MALE	-0.084	<0.001	0.818
		PERCNT_MEDCAR_ELIG	**0.066**	<0.001	0.817
		PERCNT_MEDCR_ENROL_AGED_DSBL_HI	-0.082	<0.001	0.935
		PERCNT_MEDCR_ENROL_AGED_DSBL_SMI	-0.084	<0.001	0.933
		PERCNT_MEDCR_ENROL_AGED_DSBL_TOT	-0.082	<0.001	0.935
		PERCNT_WH_MALES_65_PLUS	**0.95**	<0.001	0.885
SHORT TERM NURSING FACILITIES		PERCNT_POP_SNF	0.077	<0.001	0.856
		RATE_SNF_CERT_BEDS	0.076	<0.001	0.972
		RATE_SNF_TOT_BEDS	0.073	<0.001	0.971
AGE STRUCTURE + MEDICARE PART D		Age_85_and_Over	-0.047	0.009	0.926
		PERCNT_MEDCAR_DRUG_ENROL	0.196	<0.001	0.869
		PERCNT_WH_FEMALES_65_PLUS	0.2	<0.001	0.922

HOSPITAL CAPACITY-BEDS/SUR/ICU	**Healthcare Infrastructure- Hospitals**	Gen_Hosp_Bed_300_rate	-0.021	0.253	0.661
		RATE_ALC_CHEM_DEPEND_BEDS	-0.001	0.954	0.492
		RATE_BASSINETS	-0.02	0.274	0.759
		RATE_CARD_INTSV_CARE_BEDS	-0.024	0.185	0.779
		RATE_COMM_HOSP_ADM	0.003	0.854	0.951
		RATE_HOSP_ADMISSION	0.007	0.678	0.953
		RATE_ISOLATION_RMS	-0.039	0.031	0.682
		RATE_MED_SRG_ADULT_BEDS	0.046	0.011	0.664
		RATE_MED_SRG_PED_BEDS	-0.008	0.65	0.849
		RATE_NEONAT_INTSV_BEDS	-0.037	0.04	0.847
		RATE_OBSTET_BEDS	-0.037	0.04	0.845
		RATE_OP_ROOMS	-0.029	0.103	0.863
		RATE_OTH_INTENSV_CARE_BEDS	-0.015	0.392	0.642
		RATE_SHRTTERM_HOSP_ADM	0.008	0.65	0.953
		RATE_SURG_OPS_INPT	-0.017	0.337	0.9
		RATE_SURG_OPS_OUTPT	-0.013	0.46	0.832
		RATE_SURG_OPS_TOTAL	-0.016	0.383	0.909
HOSPITAL CAPACITY-BEDS ONLY		RATE_COMM_HOSP_BEDS	-0.009	0.625	0.97
		RATE_HOSP_BEDS	-0.007	0.713	0.926
		RATE_LICENS_HOSP_BEDS	-0.01	0.574	0.871
		RATE_LICENS_SHRTRM_HOSP_BEDS	-0.011	0.522	0.915
		RATE_SHRTTERM_HOSP_BEDS	-0.006	0.736	0.971
		RATE_TOTAL_INPT_BEDS	0.002	0.897	0.954

HOSPITAL CAPACITY-NH BEDS		RATE_LICENS_NH_HOSP_BEDS	-0.031	0.081	0.975
		RATE_LICENS_SHRTRM_NH_HOSP_BEDS	-0.028	0.12	0.972
		RATE_NURSHOME_HOSP_ADM	-0.033	0.068	0.685
		RATE_SHRTTERM_NH_HOSP_BEDS	-0.026	0.141	0.977
		RATE_TOT_NH_HOSP_BEDS	-0.03	0.094	0.98
HOSPITAL CAPACITY - OUTPAT VIS/ ICU BEDS		RATE_INTSV_CARE_BEDS	-0.023	0.21	0.691
		RATE_OUTPT_VISITS_GENHOSP	-0.033	0.068	0.97
		RATE_OUTPT_VISITS_OTH	-0.046	0.01	0.958
POLITICS	**White Marriage and Housing Stock and Politics**	Av_Per_Dem	-0.006	0.753	-0.998
		Av_Per_Rep	0.017	0.336	0.998
		Per_Dem_04	0.049	0.006	-0.97
		Per_Dem_08	-0.055	0.002	-0.978
		Per_Rep_04	-0.035	0.053	0.98
		Per_Rep_08	0.064	<0.001	0.98
WHITE MARRIAGE STATUS/ WHITE HOUSING STOCK		Housing_Owner_W	0.181	<0.001	-0.73
		Housing_Rent_W	-0.181	<0.001	0.73
		Marital_Status_Mar_W	-0.005	0.782	-0.919
		Marital_Status_Mar_WF	-0.019	0.285	-0.834
		Marital_Status_Mar_WM	0.009	0.608	-0.869
		Marital_Status_Sing_W	-0.163	<0.001	0.925
		Marital_Status_Sing_WF	**-0.214**	<0.001	0.864
		Marital_Status_Sing_WM	-0.143	<0.001	0.899

WHITE EDUCATION/ INCOME	**White Affluence Education, Family Structure, Disability and Food Insecurity**	**BC_W**	**0.388**	<0.001	-0.863
		BC_WM	**0.404**	<0.001	-0.881
		Educ_Col_F_W	**-0.0484**	<0.001	0.918
		Educ_Col_M_W	**-0.489**	<0.001	0.944
		Median_House_Inc_W	**-0.378**	<0.001	0.826
		PERCNT_WHCOLLAR_WRKR	**-0.452**	<0.001	0.858
		Per_Cap_Inc_W	**-0.453**	<0.001	0.886
		edhighwt	**-0.494**	<0.001	0.938
		mhhinwt	**-0.34**	<0.001	0.793
WHITE POVERTY		**Income_Less_Pov_W**	**0.273**	<0.001	0.903
		MED_HH_INC	**-0.459**	<0.001	-0.864
		povwt	**0.247**	<0.001	0.924
DISABILITY		**PERCNT_MEDCR_ENROL_DISABL_HI**	**0.436**	<0.001	0.987
		PERCNT_MEDCR_ENROL_DISABL_SMI	**0.442**	<0.001	0.985
		PERCNT_MEDCR_ENROL_DISABL_TOT	**0.436**	<0.001	0.987
		SNAP_W	**0.348**	<0.001	0.794
WHITE LOW EDUCATION		**Educ_Less_HS_F_W**	**0.476**	<0.001	0.959
		Educ_Less_HS_M_W	**0.484**	<0.001	0.964
		edlowwt	**0.5**	<0.001	0.974
WHITE DIVORCE		Marital_Status_SWD_W	0.255	<0.001	0.999
		Marital_Status_SWD_WF	**0.242**	<0.001	0.906
		Marital_Status_SWD_WM	**0.213**	<0.001	0.883
FOOD		**PCT_FREE_LUNCH08**	**0.495**	<0.001	0.869

INSECURITY		**PCT_POV_LT18**	**0.464**	<0.001	0.927
		PERCNT_FOODSTAMP_RECIPNTS	**0.522**	<0.001	0.935
		PERCNT_MEDCD_ELIG_FEMALES	**0.458**	<0.001	0.945
		PERCNT_MEDCD_ELIG_MALES	**0.445**	<0.001	0.944
		PERCNT_MEDCD_ELIG_TOT	**0.461**	<0.001	0.956
		POV_RATE	**0.477**	<0.001	0.913
Pollution and Heat	**Climate and Pollution**	**AvgDailyMaxHeatIndexF**	**0.49**	<0.001	0.939
		DM_Heat	**0.461**	<0.001	0.911
		NOR_FPM_H_2	**0.537**	<0.001	0.903
		Pollution_Heat_Index	**0.553**	<0.001	0.955
		land_surf_night	**0.377**	<0.001	0.859
TEMPERATURE		**DAYS_HI_100**	**0.269**	<0.001	0.911
		DAYS_HI_90	**0.331**	<0.001	0.974
		DAYS_MX_T_90	0.134	<0.001	0.882
		DM_Temp	**0.297**	<0.001	0.928
BLACK POPULATION		**BPRTRATE**	**0.488**	<0.001	0.834
		Iblack2000	**0.387**	<0.001	0.922
		PCT_NHBLACK08	**0.468**	<0.001	0.979
		PERCNT_AFRICAN_AM_POP	**0.464**	<0.001	0.981
ENVIRONMENT/ NO S/ PM/ VOLATILE/ POP DENSITY/ WHITES -No CAR		Nitrogen_Oxides_NEI_Sum_LBSQM	-0.064	<0.001	0.828
		Nitrous_Oxide_NEI_Sum_LBSQM	**-0.21**	<0.001	0.861
		PM2_5_Primary_Filt__Cond_NEI_Mean_LBSQM	-0.023	0.209	0.892
		PM_Condensible_NEI_Mean_LBSQM	-0.015	0.455	0.633

		Population_Density	-0.13	<0.001	0.888
		Volatile_Organic_Compounds_NEI_Mean_LBSQM	-0.024	0.178	0.851
		nocarwt	0.057	0.002	0.654
FOOD-FRUIT/ VEG/ MEAT/ PREP FRUIT AND VEG		**FRUVEG_PREPFOOD**	**-0.233**	<0.001	0.952
		PC_FRUVEG	**-0.21**	<0.001	0.891
		PC_MEAT	0.062	0.001	0.84
PHYSICIANS (INTERNAL MED & SPECIALTIES- ANEST, CARDIO, NEURO & SURG)		**RATE_ACTMDS_FEDNONFED**	**-0.263**	<0.001	0.985
		RATE_ACTMDS_NONFED	**-0.262**	<0.001	0.986
		RATE_ANEST_TOT_PC	**-0.263**	<0.001	0.883
		RATE_CARDIO_TOT_PC	-0.161	<0.001	0.892
		RATE_DERM_TOT_PC	**-0.202**	<0.001	0.805
		RATE_GASTRO_TOT_PC	-0.173	<0.001	0.851
		RATE_INTMED_SPEC_TOT_PC	-0.181	<0.001	0.884
		RATE_INTMED_TOT_PC	**-0.218**	<0.001	0.89
		RATE_MDS_PC_HOSP_RES	-0.104	<0.001	0.827
		RATE_MDS_PC_OFFBASED	**-0.29**	<0.001	0.927
		RATE_MDS_SPEC_TOT_PC	**-0.218**	<0.001	0.977
		RATE_MDS_TOT_PTCARE_NONFED	**-0.266**	<0.001	0.982
		RATE_MDS_TOT_SPEC_HOSP_RES	-0.109	<0.001	0.816
		RATE_MDS_TOT_SPEC_OFFBASED	**-0.235**	<0.001	0.936
		RATE_NEURO_TOT_PC	-0.163	<0.001	0.848
		RATE_NEURSURG_TOT_PC	-0.128	<0.001	0.714
		RATE_OTOLARYN_TOT_PC	-0.126	<0.001	0.787

		RATE_PATH_TOT_PC	-0.173	<0.001	0.87
		RATE_PEDS_SPEC_TOT_PC	-0.099	<0.001	0.725
		RATE_PEDS_TOT_PC	**-0.224**	<0.001	0.829
		RATE_PSYCH_TOT_PC	**-0.283**	<0.001	0.773
		RATE_PULM_TOT_PC	-0.145	<0.001	0.774
		RATE_RADONC_TOT_PC	-0.157	<0.001	0.714
		RATE_SURG_GEN_TOT_PC	-0.147	<0.001	0.792
		RATE_SURG_SPEC_TOT_PC	**-0.227**	<0.001	0.933
HSNF/ TMR		HSNF_Age_Sex_Race_Adj_05	0.124	<0.001	0.945
		HSNF_Price_Age_Sex_Race_Adj_05	0.229	<0.001	0.95
		TMR_Age_Sex_Race_Adj_05	0.131	<0.001	0.95
		TMR_Price_Age_Sex_Race_Adj_05	**0.25**	<0.001	0.947
INFANT MORTALITY		**IM_Neonatal**	**0.305**	<0.001	0.806
		IM_Postneonatal	**0.333**	<0.001	0.73
		IM_Wh_Non_Hisp	**0.239**	<0.001	0.909
		Infant_Mortality	**0.395**	<0.001	0.958
		W_Infant_Mort_Rate_99_08	**0.375**	<0.001	0.801
DISTANCE TO GROCERY/ DRIVING		PCT_HHNV10MI	0.066	<0.001	0.875
		PCT_HHNV1MI	**0.468**	<0.001	0.722
		PCT_LOWI10MI	-0.01	0.568	0.824
		PCT_LOWI1MI	**0.38**	<0.001	0.866
PHYSICIAN FAM MED & GPS		PERCENT_FAM_MED_45_64YR	-0.016	0.402	-0.936
		PERCENT_FAM_MED_UNDER_45YR	-0.047	0.013	0.943

		PERCENT_TOT_GPS_45_64YR	-0.037	0.045	-0.914
		PERCENT_TOT_GPS_UNDER_45YR	**-0.73**	<0.001	0.926
POPULATION SIZE		**POP**	**-0.225**	<0.001	0.97
		TOTPOP_2005	-0.194	<0.001	0.97
POP WHITE AND HISPANIC/ LOW LIT		**Iwhite2000**	**-0.208**	<0.001	-0.913
		PCT_HISP08	**-0.271**	<0.001	0.83
		PCT_NHWHITE08	-0.179	<0.001	-0.921
		PERCNT_HISPANIC_POP	**-0.263**	<0.001	0.824
		PERCNT_NONENG_SPEAK_OVER18YRS	**-0.222**	<0.001	0.792
		PERCNT_WHITE_POPULATION	**-0.349**	<0.001	-0.71
		Per_Low_Literacy	**0.287**	<0.001	0.825
RURAL ENVIRONMENT		PERCNT_AGR_FRST_MIN_WRLR	-0.023	0.197	0.798
		PERCNT_RURAL_FARM	-0.065	<0.001	0.969
		PERCNT_RURAL_NONFARM	0.065	<0.001	-0.969
ENVIRONMENTAL/ PM		PM10_Filterable_NEI_Mean_LBSQM	-0.062	0.001	0.971
		PM10_Primary_Filt__Cond_NEI_Mean_LBSQM	-0.055	0.002	0.954
		PM2_5_Filterable_NEI_Mean_LBSQM	-0.011	0.528	0.938
CRIME		Grndtot_rate	0.004	0.851	0.873
		p1prpty_rate	-0.066	0.006	0.961
		p1tot_rate	-0.033	0.165	0.964
HOSPITAL F/T STAFF		RATE_MDS_OTHMED_HSP_FT	-0.12	<0.001	0.82
		RATE_MDS_OTHSPEC_HSP_FT	-0.115	<0.001	0.863
		RATE_MDS_TOT_PC_HOSP_FT	-0.107	<0.001	0.917

MEDICARE ELIGIBILITY		PERCNT_MEDCR_ENROL_AGED_HI	-0.157	<0.001	0.996
		PERCNT_MEDCR_ENROL_AGED_SMI	-0.162	<0.001	0.986
		PERCNT_MEDCR_ENROL_AGED_TOT	-0.151	<0.001	0.995
PHYSICIANS RATE FAM MED & GP		RATE_MDS_FM_TOT_PC	-0.173	<0.001	0.981
		RATE_MDS_GP_TOT_PC	-0.156	<0.001	0.982
		RATE_MDS_TOT_FM_OFFBASED	-0.172	<0.001	0.982
		RATE_MDS_TOT_GP_OFFBASED	-0.155	<0.001	0.981
BLACK MARRIAGE STATUS		Marital_Status_Mar_B	-0.051	0.006	0.895
		Marital_Status_Mar_BM	-0.03	0.117	0.91
		Marital_Status_Sing_B	-0.036	0.054	-0.888
		Marital_Status_Sing_BM	-0.019	0.307	-0.907
PHYSICIANS DO		RATE_ACTV_DO_FEDNONFED	-0.062	0.001	0.987
		RATE_ACTV_DO_NONFED	-0.064	<0.001	0.988
		RATE_DO_TOT_PTCARE	-0.062	0.001	0.948
PHYSICIAN INTERNAL MED & SPECIALTIES PROVIDER AGE		PERCENT_GEN_INTMED_45_64YR	-0.044	0.036	0.934
		PERCENT_GEN_INTMED_UNDER_45YR	-0.052	0.014	-0.934
		PERCENT_MED_SPEC_45_64YR	-0.064	0.002	0.935
		PERCENT_MED_SPEC_UNDER_45YR	-0.095	<0.001	-0.933
WIC PROGRAM		PCH_REDEMP_WICS	-0.018	0.341	-0.643
		PCH_WICS	-0.063	0.001	0.966
		PCH_WICSPTH	-0.051	0.005	0.966
NO HEALTH INSURANCE		PERCNT_FEMALES_LT65_NO_HLTH_INS	-0.178	<0.001	0.989
		PERCNT_LT65_NO_HLTH_INS	-0.178	<0.001	1
		PERCNT_MALES_LT65_NO_HLTH_INS	-0.171	<0.001	0.99

Table 3. Latent Construct High Obesity County Relationships (all variables correlate to obesity with r> 0.430)

Original Paraclique Cluster	Latent Construct Cluster	Latent Construct	Variables Included	Factor loading on Latent Construct
Healthcare Infrastructure, Providers, and Crime	**Healthcare Infrastructure & Providers**	**PHYSICIAN PROVIDERS** ***Alpha= 0.987***	RATE_ACTMDS_FEDNONFED	0.984
			RATE_ACTMDS_NONFED	0.985
			RATE_ANEST_TOT_PC	0.891
			RATE_MDS_PC_OFFBASED	0.959
			RATE_MDS_SPEC_TOT_PC	0.963
			RATE_MDS_TOT_PTCARE_NONFED	0.988
			RATE_MDS_TOT_SPEC_OFFBASED	0.948
			RATE_OPTH_TOT_PC	0.846
			RATE_SURG_SPEC_TOT_PC	0.95
		PHYSICAN SPECIALITY PROVIDERS	RATE_PLASTIC_TOT_PC	NA
White Affluence and Education		**WHITE INCOME** **Alpha= 0.949**	mhhinwt	0.954
			Median_House_Inc_W	0.977
			Per_Cap_Inc_W	0.928
		WHITE POVERTY **Alpha=0.878**	Income_Less_Pov_W	0.935
			SNAP_W	0.864
			povwt	0.891
		WHITE HIGH EDUCATION	Educ_Col_F_W	0.974
			Educ_Col_M_W	0.977

		Alpha=0.978	edhighwt	0.984
Population and Pollution		**URBANICITY & POLLUTION**	Nitrous_Oxide_NEI_Sum_LBSQM	NA
		POPULATION SIZE	POP	NA
Poverty, Disability Climate, Pollution and Minority Population Interaction	**Quality of Life From Birth**	**DEPRIVATION Alpha=0.860**	PERCNT_MEDCD_ELIG_MALES	0.852
			PERCNT_MEDCR_MEDCD_DUAL_ELIG	0.842
			Under_18	0.864
			f_divorce	0.801
		AVERAGE LIFE EXPECTANCY	ALE	NA
	Majority Population, Political Engagement & Births To Unmarried Women	**MAJORITY POPULATION**	PERCNT_WHITE_POPULATION	NA
		BIRTHS TO UNMARRIED WOMEN	Unmarried	NA
	High Percent Black Population, Segregation, With Poor Birth Outcomes	**% BLACK POPULATION, SEGREGATION, POOR BIRTH OUTCOMES** ***Alpha = 0.926***	Iblack2000	0.906
			LBW	0.867
			PCT_NHBLACK08	0.945
			PERCNT_AFRICAN_AM_POP	0.946
			Per_Low_Literacy	0.643
			Premature	0.815
		WHITE ISOLATION	Iwhite2000	NA
	ality, Food Access & Diabe	**INEQUALITY, FOOD ACCESS & DIABETES**	PCT_DIABETES_ADULTS	0.891

		Alpha = 0.741	PCT_HHNV1MI	0.891
	Poverty Public Assistance & Income	**MEDIAN HOUSEHOLD INCOME ALL POPULATION**	MED_HH_INC	NA
		POVERTY Alpha=0.957	PCT_FREE_LUNCH08	0.877
			PCT_POV_LT18	0.95
			PERCHLDPOV	0.759
			PERCNT_FOODSTAMP_RECIPNTS	0.92
			PERCNT_MEDCD_ELIG_FEMALES	0.899
			PERCNT_MEDCD_ELIG_TOT	0.906
			PERSIST_POVERTY	0.721
			POV_RATE	0.94
		FOOD HABITS & COST – Fruit/ Vegetables/ Processed Snacks	PC_FRUVEG	NA
		CLIMATE Alpha= 0.963	AvgDailyMaxHeatIndexF	0.871
			DAYS_HI_100	0.874
			DAYS_HI_90	0.972
			DM_Heat	0.886
			DM_Temp	0.945
			Temp_min	0.892
			land_surf_night	0.674
		HEAT, POLLUTION & PRECIPITATION	NOR_FPM_H_2	0.943
			Pollution_Heat_Index	0.949

		Alpha = 0.876	precip	0.791
LOW WHITE EDUCATION, HIGH DISABILITY & WORKING FEMALES		**LOW WHITE EDUCATION AND HIGH DISABILITY** ***Alpha = 0.959***	Educ_Less_HS_F_W	0.884
			edlowwt	0.899
			PERCNT_MEDCR_ENROL_DISABL_HI	0.957
			PERCNT_MEDCR_ENROL_DISABL_SMI	0.96
			PERCNT_MEDCR_ENROL_DISABL_TOT	0.957
			Health_Status	0.887
		FEMALE LABORFORCE ***Alpha = 1.000***	Laborforce16_64_BF	1
			Laborforce16_64_WF	1
		WHITE BLUE COLLAR WORKERS Alpha=0.982	BC_W	0.991
			BC_WM	0.991
Phyicians DO		**PHYSCIANS DO**	rate_actv_do_nonfed	NA

Table 4. Latent Construct Low Obesity County Relationships (all variables correlate to obesity with r> 0.290)

Original Paraclique Cluster	Latent Construct Cluster	Latent Construct	Variables Included	Factor loading on Latent Construct
Age, Aging and Aging Infrastructure	Male Age & Medicare	**Male Age Structure+ Medicare Eligibility Alpha = 0.824**	PERCNT_MEDCAR_ELIG	0.927
			PERCNT_WH_MALES_65_PLUS	0.927
White Marriage Status/ White Housing Stock		**White Marriage Status/ White Housing Stock**	Marital_Status_Sing_WF	NA
White Affluence Education, Family Structure, Disability and Food Insecurity	White Education/ Income	**Blue Collar Whites Alpha = 0.945**	BC_W	0.960
			BC_WM	0.960
		White Workers Education and Income Alpha = 0.503	Educ_Col_F_W	0.938
			Educ_Col_M_W	0.949
			Median_House_Inc_W	0.830
			PERCNT_WHCOLLAR_WRKR	0.853
			Per_Cap_Inc_W	0.899
			edhighwt	0.952
	White Poverty	**White Poverty Alpha = 0.878**	Income_Less_Pov_W	0.944
			povwt	0.944
		Median Household Income All Population	MED_HH_INC	NA
		Disability Alpha = 0.896	mhhinwt	0.987
			PERCNT_MEDCR_ENROL_DISABL_SMI	0.985
			PERCNT_MEDCR_ENROL_DISABL_TOT	0.987

		White-Low Education Alpha = 0.959	Educ_Less_HS_F_W	0.959
			Educ_Less_HS_M_W	0.964
			edlowwt	0.974
		White Divorce Alpha = 0.751	Marital_Status_SWD_WF	0.895
			Marital_Status_SWD_WM	0.895
		Food Insecurity Alpha = 0.947	PCT_FREE_LUNCH08	0.869
			PCT_POV_LT18	0.927
			PERCNT_FOODSTAMP_RECIPNTS	0.935
			PERCNT_MEDCD_ELIG_FEMALES	0.945
			PERCNT_MEDCD_ELIG_MALES	0.944
			PERCNT_MEDCD_ELIG_TOT	0.956
			POV_RATE	0.913
Climate and Pollution	**Pollution and Heat**	**Climate Alpha = 0.932**	AvgDailyMaxHeatIndexF	0.939
			DM_Heat	0.911
			NOR_FPM_H_2	0.903
			Pollution_Heat_Index	0.955
			land_surf_night	0.859
		Temperature Alpha = 0.945	DAYS_HI_100	0.925
			DAYS_HI_90	0.987
			DM_Temp	0.935
Black Population		**Black Population Alpha = 0.719**	BPRTRATE	0.834
			Iblack2000	0.922
			PCT_NHBLACK08	0.979
			PERCNT_AFRICAN_AM_POP	0.981
Environment/ NO S/ PM/ Volatile/ Pop Density/ Whites -No Car	**Pollutant Nitrous Oxide**	**Environment/ Nitrous Oxide**	Nitrous_Oxide_NEI_Sum_LBSQM	NA

Food-Fruit/ Veg/ Meat/ Prep Fruit And Veg	Fruit / Veggie Cost	**Food-Fruit/ Veg/ Meat/ Prep Fruit & Veg Alpha = 0.903**	FRUVEG_PREPFOOD	0.955
			PC_FRUVEG	0.955
Physicians (Internal Med & Specialties- Anest, Cardio, Neuro & Surg		**Physicians (Internal Med & Specialties-Anest, Cardio, Neuro & Surg) Alpha = 0.921**	RATE_ACTMDS_FEDNONFED	0.987
			RATE_ACTMDS_NONFED	0.987
			RATE_ANEST_TOT_PC	0.882
			RATE_DERM_TOT_PC	0.794
			RATE_INTMED_TOT_PC	0.913
			RATE_MDS_PC_OFFBASED	0.959
			RATE_MDS_SPEC_TOT_PC	0.977
			RATE_MDS_TOT_PTCARE_NONFED	0.989
			RATE_MDS_TOT_SPEC_OFFBASED	0.961
			RATE_PEDS_TOT_PC	0.868
			RATE_PSYCH_TOT_PC	0.802
			RATE_SURG_SPEC_TOT_PC	0.937
HSNF/ TMR		**HSNF/ TMR**	TMR_Price_Age_Sex_Race_Adj_05	NA
Infant Mortality		**Infant Mortality Alpha = 0.054**	IM_Neonatal	0.806
			IM_Postneonatal	0.73
			IM_Wh_Non_Hisp	0.909
			Infant_Mortality	0.958
			W_Infant_Mort_Rate_99_08	0.801
DISTANCE TO GROCERY/ DRIVING		**Distance to Grocery/ Driving Alpha = 0.869**	PCT_HHNV1MI	0.94
			PCT_LOWI1MI	0.94

Physician Fam Med & GPS		**Young General Practice Physicians**	PERCENT_TOT_GPS_UNDER_45YR	NA
Population		**Population**	POP	NA
Pop White And Hispanic/ Low Lit	**Hispanic and Low Literacy**	**Hispanic Pop/ Low Lit Alpha = 0.848**	Per_Low_Literacy	0.723
			PCT_HISP08	0.962
			%_HISPANIC_POP	0.952
			% NONENG SPEAK OVER18YRS	0.923
	White Isolation	**White Population/Segregation Alpha=0.935**	Iwhite2000	0.969
			PERCNT_WHITE_POPULATION	0.969

Figure1

Figure 1. High Obesity Paracliques that Represent County Relationships (Disconnected paracliques that do not have any variables that correlate with obesity are not shown)

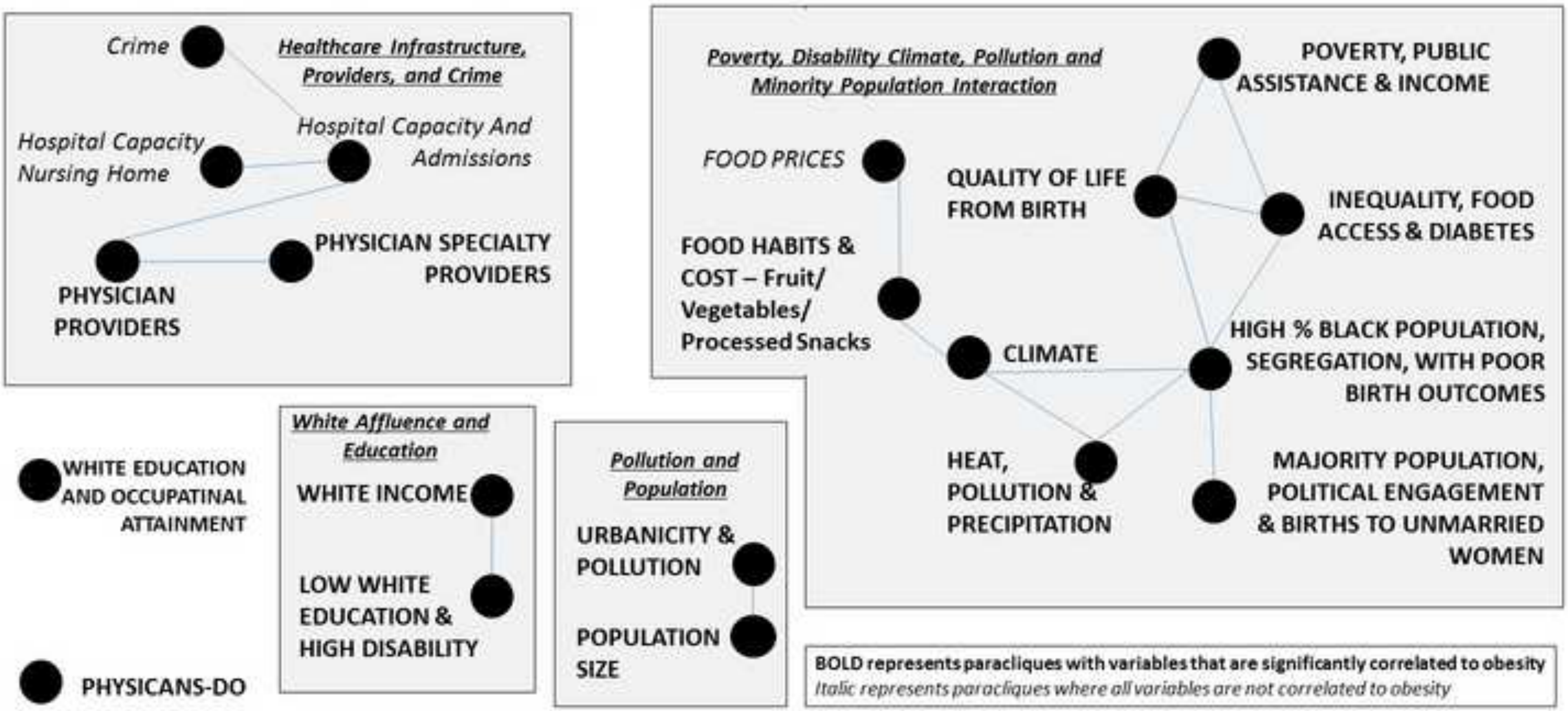

Figure2

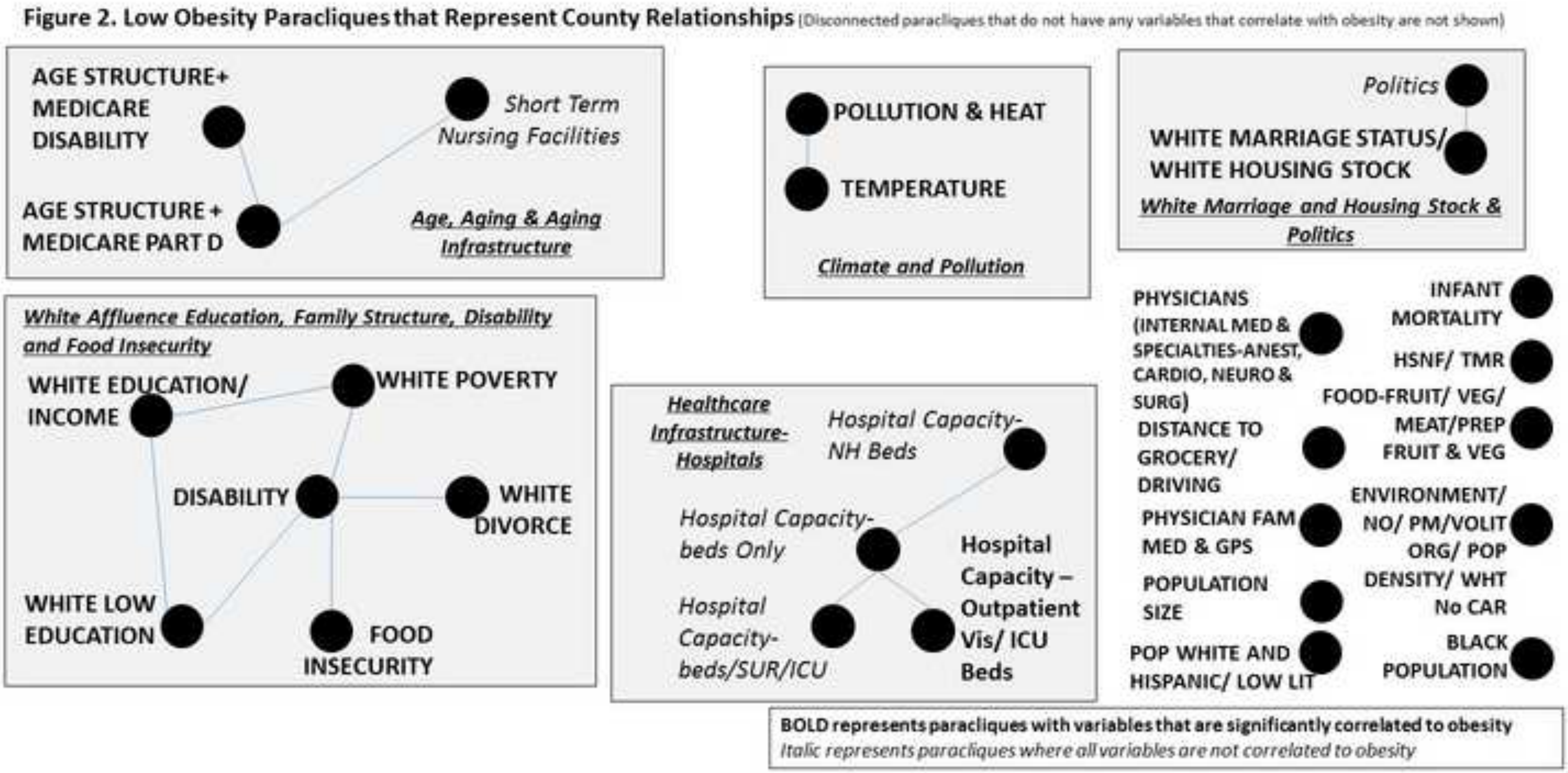
Figure 2. Low Obesity Paracliques that Represent County Relationships (Disconnected paracliques that do not have any variables that correlate with obesity are not shown)
AGE STRUCTURE+ MEDICARE DISABILITY
Short Term Nursing Facilities
AGE STRUCTURE + MEDICARE PART D
Age, Aging & Aging Infrastructure
POLLUTION & HEAT
TEMPERATURE
Climate and Pollution
Politics
WHITE MARRIAGE STATUS/ WHITE HOUSING STOCK
White Marriage and Housing Stock & Politics
White Affluence Education, Family Structure, Disability and Food Insecurity
WHITE EDUCATION/ INCOME
WHITE POVERTY
DISABILITY
WHITE DIVORCE
WHITE LOW EDUCATION
FOOD INSECURITY
Healthcare Infrastructure-Hospitals
Hospital Capacity-NH Beds
Hospital Capacity-beds Only
Hospital Capacity-beds/SUR/ICU
Hospital Capacity – Outpatient Vis/ ICU Beds
PHYSICIANS (INTERNAL MED & SPECIALTIES-ANEST, CARDIO, NEURO & SURG)
DISTANCE TO GROCERY/ DRIVING
PHYSICIAN FAM MED & GPS
POPULATION SIZE
POP WHITE AND HISPANIC/ LOW LIT
INFANT MORTALITY
HSNF/ TMR
FOOD-FRUIT/ VEG/ MEAT/PREP FRUIT & VEG
ENVIRONMENT/ NO/ PM/VOLIT ORG/ POP DENSITY/ WHT No CAR
BLACK POPULATION
BOLD represents paracliques with variables that are significantly correlated to obesity
Italic represents paracliques where all variables are not correlated to obesity

Figure3

Figure 3. Latent Construct High Obesity County Relationships (all variables correlate to obesity with r> 0.430)

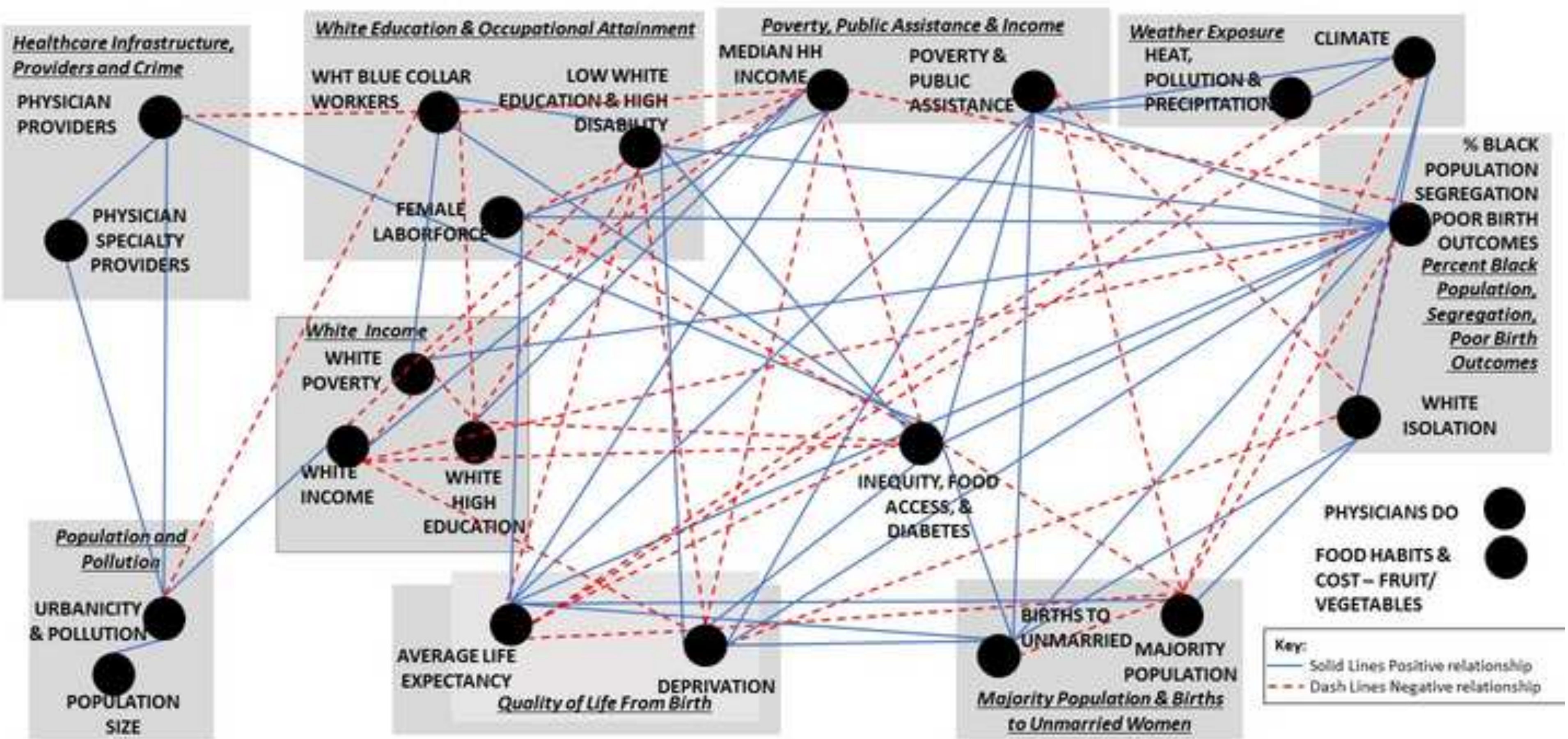

Figure 4

Figure 4. Latent Construct Low Obesity County Relationships (all variables correlate to obesity with r> 0.290)