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The Proclivity of Certain Common Societal Traits in North Carolina Counties and Their Proposed Impact on the County's Overall Well-being

(2012-2016)

Abstract

Objective: To identify potential correlation between the prevalence of a few common societal behaviors exhibited in a particular county, and conclude whether they play a substantial role in the county's aggregate perceived health. If correlation is found, additional time should be spent identifying potential county initiatives to counteract the negative impact had on the county's self-reported well-being.

Methods: Created a regression model hoping to extract correlation between the included independent and dependent variables. Three major societal behaviors were included as independent variables (physical inactivity, obesity level, excess drinking). Also, additional variables hoping to control for demographic, socio-economic, and county provided resources (access to exercise and limited access to healthy foods) were included. Three dependent variables were also incorporated with the hope of encompassing all sectors of self-perceived health. All data used in this test were provided by *County Health Rankings & Roadmaps.*

Results: Physical inactivity showed to have a significant, negative impact on all three measurements of a county's well-being. Obesity levels curtailed counter-intuitive results. It seems that the issue lies in the characterization of obesity, as the inefficient BMI measurement was used. Excessive drinking showed inconclusive results on its impact on physical health, however, it did illustrate significant correlation to worsening mental health. Access to exercise opportunity exhibited relation in both the number of poor mental and physical health days, indicating an increase in opportunity should lead to improved well-being. Limited access to healthy foods proved to provide counter-intuitive results.

Conclusion: Based on previous research, as well as the results of this test, counties should look to implement policy that would increase the resident's activity level, as well as limit excess alcohol consumption. Based on the results found providing additional exercise opportunity is recommended.

Introduction

Physical ailments, illnesses, and mental distress are an unavoidable part of human reality, and will be experienced by everyone at some point in their life. Regardless, it is a point by most to limit these occurrences. Genetic make-up of the individual plays a large role in their health, however, where they live and what behavioral tendencies they partake in can play a substantial part in their overall health. In this study, overall well-being is a personal perceptive measure; it is how the individual feels about their own health. While being identified as ill or suffering of ailment would greatly effect a person's well-being, it does not need to be verified by a medical professional or be a diagnosis; it is a person's particular impression of their health. That being said, it is worth time and resources to identify some of these key behavioral traits that are generally associated with an individual's health. This research hopes to better recognize the correlation between the prevalence of a few common societal behaviors in a particular county, and conclude whether they play a substantial role in the county's aggregate perceived health. In addition, time should be spent gathering information on particular communal resources and detecting if they are correctly apportioned to best impact their populace's perceived health.

Implications: It is intuitive to comprehend that feelings of physical or mental distress puts a strain on the individual who is suffering, and has potential to derail them economically if the anguish is long standing. Poor health is not only the plight of the individual. There are serious implications to local, or on a grander scale, national level economies. Health care costs, as well as the cost taken on by firms when required to provide their worker's benefits, are only a few of the direct costs that can be associated to poor health. There are also numerous, many times unseen, additional expenses that take a toll on companies. An article found on *Forbes* website, which was written in 2012 by Bruce Japsen, speaks on the price of poor health along with better identifying one of these un-assumed costs. According to Japsen, poor health costs the U.S. economy approximately $576 billion a year. Of this total, $227 billion, or 39% of this cost is associated with the phenomena aptly named “presenteeism”. “Presenteeism” is the loss of productivity do to employees working while ill, which prevents them from performing at their top efficiency. A reasonable conclusion from the existence of this occurrence is that many times undenounced to an employer, a portion of their labor force may be producing at a reduced rate.

The reported national monetary cost is monumental, however, these results are missing a key faction of the population in distress. An individual’s well-being can be measured by a number of different elements, and as previously stated, the standing of a person’s welfare is many respects an extremely personal estimation. While things like physical illness or impairments can be identified by external sources, other factors of health like mental ailments are less quantifiable, and thus left out of many cost estimations. Also, mental distress can lead to copious, and in many cases sever, indirect costs. An article found in <u>The American Journal of Psychiatry,</u> which was titled *Assessing the Economic Costs of Severe Mental Illness* and written by M.D. Thomas R. Insel, mentions a number of these indirect costs that may not intuitively be thought to have been included in the total. Reduced labor supply, public income support payments, a reduction in educational attainment, and also costs associated with incarceration or homelessness are all additional contributors to inefficient national markets caused by crippling metal illness. The idea of “presenteeism” is again applicable. Mental illness aside;

distresses such as stress, prolonged anger, or deepening sadness can be debilitating in their own right. With these in tow, simple daily activities can be difficult to accomplish, let alone performing at maximum capacity in the workplace.

Stifling monetary loss is an important benefactor of identifying behaviors that negatively impact health, however, simply identifying these instigators will not reduce their influence. Acting on this knowledge appropriately, and concisely is necessary in order to change the prevalence of the behavior in a community. Looking particularly at the societal vice of excess drinking; if a correlation is found between this behavior and worsening health then communities have an opportunity to act on this information and implement policy towards reduction. A paper published by Peter D'Abbs and Samantha Togni in 2000 spoke on the impact alcohol restrictive policies had on the consumption of alcohol in Rural Australia. The research looked at data of four counties that had previously implemented community initiatives to limit alcohol consumption, and then looked for changes in alcohol related indices including consumption, alcohol-related injuries, and economic activities. They found that there was real impact on alcohol consumption as well as injuries caused by excess alcohol consumption. There is research that shows policy can reduce alcohol consumption. While their research did not identify the policies direct effect on the community's well-being, it is logical to deduce that if alcohol use is significantly correlated with a reduction in perceived health, its reduction would result in an increase to overall well-being. In this research two additional communal resources have been included, access to exercise opportunity and limited access to healthy foods, in the hopes to identify if their inclusion impacts county aggregate perceived health.

Background: Research with the intent to identify significant correlations, or even no correlation between certain common, societal factors and their impact on health is not uncommon. Dr. Kenneth R. Fox from the University of Bristol, UK wrote an interesting paper looking into the influence of physical activity on mental well-being. In his research he collected the results from numerous studies, all finding significant improvements in the participant's various mentally distressed states. Increased physical activity to a safe range showed to reduce anxiety, stress, and depression while also improving the participant's cognitive abilities (reaction time, memory, and fluid intelligence), sleep quality, and numerous other overall health factors. Despite these promising results, there were a few research issues identified. Dr. Fox spoke on the lack of research in this field, and the research that has been done has been by individuals who find themselves in fields such as exercise or sport and health science. While they are undeniably reliable sources on identifying the health of an individual, they are not in principles based in research so fallacies such as not randomizing controlled studies correctly or taking cost effective measures are sure to be present. Another potential snag in the data that he mentions, which could also pertain to this research, is the problem with using self-reported results. Only willing participants contribute, which may result in their answers containing some sort of bias. Also, the entire population may not be represented. Individuals who believe their answers to be embarrassing or wrong would not participate, thus they would not be included. Many times this portion of the population, with this type of attribute, is the intended target of the study.

Excess alcohol consumption has commonly been known to directly correlate with the individual's physical health. There also seems to be a collective idea that excessive drinking influences the person's mental state. In this case the issue of simultaneity can be discussed.

Simultaneity is an equation bias, found when the dependent variable is not truly exogenous, or it is a function of other variables. In this sample it is entirely possible that while excess drinking directly influences a person's mental state, the inverse is also true. So a person's mental state can also sway a person's proclivity towards, or away from excess drinking.

While this attribution of simultaneity can be applied to a large portion of the sample, there is a less intuitive section that are effected by higher levels of excess drinking in a county. A research paper was published on this theory in 2011. Sally Casswell, Ru Quan You, and Taisia Huckle looked into *Alcohol's harm to others: reduced wellbeing and health status for those with heavy drinkers in their lives.* They surveyed 3068 New Zealand residents aged 12-80 years old and inquired on their estimated health status, subjective well-being, and finally cross examined this with self-reports of heavy drinkers in their lives. Their results were fascinating, if not unsurprising. The findings indicated that increased exposure to heavy drinkers led to a lower health status along with inferior personal well-being. This should be considered when looking over the results of this test. The variable of excess drinking only specified the respondent's inclination to drink. Even if the respondent answered no, their well-being could still be impacted by the excessive drinking of a loved one. Despite the county percentage of individuals affected by excessive drinking being underreported, the effect on their well-being should still be included based on the self-reporting nature of the dependent variables. An external force impacting their health will be taken into account when they answer the survey.

Method

Based on intuitiveness, as well as indications provided from previous research, theory suggests decreasing the proclivity of certain common societal traits and behaviors (excess drinking, obesity levels, physical inactivity) in a county, should result in an improved level of aggregate perceived mental, physical, and overall health in said county.

At the aggregate county level, the overall perceived health of the populace can be identified as a function of the prevalence a county's residents have towards select behavioral factors. The proposed equation is illustrated as:

$$H=\alpha+\beta' B+D+S+R$$

where H denotes the self-reported health of the populace, B encompasses the selected behaviors, D contains the demographic controls, S contains socio-economic variables, and R contains county provided resources (access to exercise and limited access to healthy foods).

Data: All of the data included in this research was gathered from The *County Health Rankings & Roadmaps* program. They are a collaboration between Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute, and hope to spread awareness of the numerous factors that influence health. The data was a result of yearly administered surveys for every county in the United States. For this research the data was collected yearly from the 100 counties found in North Carolina over a five year span starting in 2012 and ending in 2016. Not all of the data over the five years was present. Some counties did not report on certain years, and a few of the variables did not have data for all five years. A linear model was created in excel in order to fill in the missing figures.

Variables: In total sixteen independent variables were included. Physical inactivity, adult obesity, and excess drinking were the focus of the regression, as they represent three main societal behaviors that are thought to have an impact on an individual's health. Along with these, additional variables were included with the intent to control for demographic and socio-economic differences. Two measurements for the level of county infrastructure influence (access to exercise opportunities and limited access to healthy foods) were incorporated with the intent to identify if potential policy initiatives had any traction in improving the county's aggregate well-being. The entire list of variables, along with their definition, mean, standard deviation, and range can be found in figure. 1.

In order to fully encompass the entirety of each counties perceived level of health, three dependent variables were included. The first incorporated was the number of poor physical health days in the last thirty days. This report should allow the research to detect associations between the included behaviors and the average level of physical illness or injury experienced by the county. When speaking on the health of a subject, generally the first place assumed is their physical condition; mental health is placed to the back, or worse left out completely. In order to make sure of its inclusion, the number of poor mental health days in the last thirty days was also used as a dependent variable. It is recorded nearly the same manner as the previous, however, it is identifying the respondents level of stress, depression, or some form of additional emotional distress.

The final dependent variable was an overall measurement of the respondent's health. The participant was asked to rate their overall level of health as *excellent, very good, good, fair, or poor* and the percentage of the sample from each county who answered fair or poor was recorded. No stipulations were included, as an ambiguous question it was up to the respondent's interpretation. That indicates that both mental and physical ill-being would be included in the results, providing this research with an overall measurement of self-reported well-being. Obviously, similar to the concern previously mentioned, individual's interpretation of the question may lead to them to not include their mental distress as a driver in their answer. Without control over the survey, this is an unavoidable reality. However, it is reasonable to think that a portion of the respondents did include mental health in their answer, and this variable is an applicable container for both physical and mental distress. It is important to distinguish now that this variable is assumed to be weighted heavily towards representing the person's physical health; mental health statistics only encompass a small portion of the variable.

Results

As previously mentioned, an analysis was run on three differing dependent variables with the intent to cover the entirety of the health/well-being spectrum of each county. The results garnered from the model provided some intriguing verdicts. All of the included variables' coefficients and p-values, in relation to the three dependent variables tested, can be found in figure. 2. The physical inactivity level of a county was highly significant across the board; all three p-levels were well below 0.000. Additionally, all three of our health measurements garnered positive coefficients when tested against physical inactivity. This is a reasonably substantial indication that the higher the propensity of inactivity that a county has directly effects the counties overall well-being.

The two additional societal behaviors included procured less concrete results; still they provided a few noteworthy findings. Adult obesity levels only showed to be significant towards poor mental health, and even those findings were counter-intuitive to preconceived expectations. The p-value was 0.01, which implies high level of connectivity; the resulting coefficient was -0.035. This is where the test implication differs from expectation. A negative, significant correlation implies that the higher the percentage of adults who are considered obese, the lower the number of poor health days; contradictory from the expected result. Before taking this as a radical revelation it is best to look at the nature of the variable. The measurement used in the data proclaimed obesity to be any individual who had a Body Mass Index (BMI) greater than 30kg/m^2. Many challengers of BMI consider it to be an archaic method in obesity measurement. *The Department of Health and Human Services Centers for Disease Control and Prevention* (CDC) listed a few of the measurements shortcomings on their website stating, "Factors such as age, sex, ethnicity, and muscle mass can influence the relationship between BMI and body fat. Also, BMI does not distinguish between excess fat, muscle, or bone mass, nor does it provide any indication of the distribution of fat among individuals." (CDC.org). Based on these admissions from the CDC, it can be expected that a large portion of the population that is deemed obese does not truly think that they have a severe weight issue. This means they do not experience the mental distress associated with obesity, because in their mind they are not obese.

The prevalence of excess drinking showed correlation to both poor mental health days and the percentage of individuals who rated their health as poor or fare with p-values of 0.005 and 0.002 respectively. Interestingly, the trends from the two dependent variables moved in opposite direction. Poor mental health days has a coefficient of 0.029 indicating a co-movement; higher levels of excess drinking in a county should lead to a higher level of poor mental health days on average. The percentage of individuals who rated their health below average showed an inverse relationship, counter to expectations. With a coefficient of -0.173, indications point towards a higher proclivity of the residents of a county to excessively drink will actually lead to a higher perception of their supposed overall well-being. At first this seems the two results are counteracting each other. This difference in movement may very well be caused by inefficiencies in the survey that provided the data used. Concerns over the ambiguous nature of the third dependent variable used were brought up previously and these results may verify its ineptness as an overall measurement of well-being. Reiterating the prosed apprehension, the question's open-ended nature and the abstruseness of mental distress for consideration as an index for health, may lead to its lack of inclusion in the respondents answer. So it must be kept in mind that the measurement is not an equal depiction of both types of health, instead it very likely to be weighted heavily towards identifying the respondents physical health as opposed to being an all-encompassing measure. The coefficient for excess drinking in relation to poor physical health days is a positive 0.005, however, it is highly insignificant with a p-value of 0.586 which leaves reliability in this variable's relationship extremely doubtful. Another explanation of the differencing outcome of the two variables is the inclusion of individuals who are suffering from mental distress do to living with someone who drinks excessively. As established by Sally Casswell, Ru Quan You, and Taisia Huckle in their paper *Alcohol's harm to others: reduced wellbeing and health status for those with heavy drinkers in their lives,* there is direct correlation between increased exposure to heavy drinkers and a lower health status along with inferior personal well-being. This additional population would exclusively be included in the number of poor mental health days, if the proposition that the variable of poor or fair health did not adequately embody mental health.

In addition to the main inclusions, findings from the control variables should also garner some interest. Both of the included measurements for possible county initiatives, access to exercise opportunities and limited access to healthy foods, resulted in negative coefficients. Exercise opportunity showed relation in both the number of poor mental and physical health days, indicating an increase in opportunity for exercise should lead to improved well-being. Limited access to healthy foods, which is an index for both poverty as well as grocery store proximity, indicated that there was a significant correlation between the increase in limited access to healthy foods and a decrease in poor physical health. Again, this finding is counter-intuitive. Although a stretch, this could possibly be a result of the further distance away from grocery stores requiring the individual to travel farther. This could be construed as a form of exercise, although the likelihood is greater that there is an inefficiency present in the included variable. This may be a result of multicollinearity, which is when two or more independent variables are highly correlated with one-another resulting in the estimations of both variables being in-precise. This variable encompasses poverty levels, which shares many characteristics with unemployment. The inclusion of unemployment also reaped counter-intuitive findings, as the coefficients for the number of poor mental and physical health days suggests that a higher level of unemployment should lead to a higher overall level of well-being, which is contradicted by the positive coefficient found for the fair or poor health variable. This could lead to the conclusion that neither variable’s results (limited access to healthy foods and unemployment level) should be taken into consideration when analyzing the final outcome.

Some further findings of note, it seems that living in a county that is primarily rural may lead to a higher level of perceived physical injury or illness, however, it actually improves the counties aggregate reported mental health. A higher portion of residents who have or have had achieved some level of secondary education is only significantly correlated to the level of a county’s population who rated their health as fair or poor, and with a coefficient of -0.065 it slightly reduces that percentage. Living in a county located in the mountain region of the North Carolina shows indication that they will experience, on average, higher levels of poor health in all three measure when compared to counties in the piedmont or coastal regions.

Conclusion

Despite the non-conclusive nature of some of the variables tested, there was plenty of support directed towards the proposed hypothesis. High inactivity levels in a county seems to inflict a higher level of aggregate poor health and well-being across all three health measurements used. The counter-intuitive results gathered from high levels of obesity and its impact on a populaces’ health can be explained through the survey’s use of the archaic and flawed BMI measure; which should exclude the independent variable from being considered a behavioral catalyst. After identifying the lack of parity in the final dependent variable used (intended to represent both mental and physical well-being), clarification on the proclivity for a county’s population to excessively drink and it’s correlation to that county’s health became clear. While the relationships charge towards physical health changes based on how the survey question is asked, the variables impact on the county's collective mental health is easier to interpret. Its p-value of .005 indicates strong correlation and its positive coefficient endorses the hypothesis that a higher level of excess drinking leads to a higher level of mental distress.

Also to be considered when analyzing the results of this test are the potential policy implementations counties can pursue in order to limit these behavior traits impact. As mentioned, findings support the notion that physical inactivity increases an individual's personal opinion that they are in poor mental or physical health. The higher the percentage of access to exercise opportunities showed to have a significant decrease to the overall number of both poor mental and physical health days. This is a strong indication that if a county is hoping to increase their resident's well-being they should look to provide additional access to exercise opportunities. Some examples of potential implementations are an increase in parks, local youth centers, or even providing incentives for owning a gym in the county. The case study conducted by Peter D'Abbs and Samantha Togni in 2000 showed that county initiatives to reduce the consumption of alcohol in a community have been successfully implemented and have had a positive impact on the populations drinking habits. Previous research, as well as the findings in this study indicate that the drinking habits impact not only the participant's mental health, but those around them. Another possible thought for policy makers is to provide additional outreach for individuals who have a loved one struggling with excess alcohol consumption. This research does not unequivocally designate the included behaviors as direct influences on a populace's self-identified well-being. It does provide direct support towards previously established theory, as well as establishing this researches originally proposed hypothesis.

Fig. 1

Variable	Definitions	Mean (Standard Deviation)
Y1= Poor mental health days (last 30 days)	Number of days out of past 30 days the respondent felt stress, depression, and problems with emotions	3.73 (.728) (1.6-6.2)
Y2= Poor physical health days (last 30 days)	Number of days out of past 30 days the respondent felt physical illness or injury	3.995 (.682) (2-6.2)
Y3= Poor or fair health	Percent of adult respondents who rate their health "fair" or "poor"	20.04 (5.03) (9-57)
X1= Physical Inactivity	Percentage of adults (20<) reporting no leisure-time physical activity	27.666 (3.916) (15-39)
X2= Adult Obesity (%)	Percentage of the adult population (20<) that reports a body mass (BMI) greater than 30kg/m^2	30.736 (4.011) (20-41)
X3= Excess drinking	Percentage of adults who reported consuming more than 4 (women) or 5 (men) alcoholic beverages on a single occasion in the past 30 days, or heavy drinking, defined as drinking more than one (women) or 2 (men) drinks per day on average	12.168 (3.740) (4-28)
X4= Access to Exercise opportunities	Percentage of individuals in a county who live reasonably close to a park or recreational facilities	58.474 (25.331) (0-115)
X5= Limited access to healthy foods	Percentage of the population that is low income and does not live close to a grocery store. (rural=10 miles; urban=1 mile)	5.31 (4.085) (0-26)
X6= Unemployment (%)	Percentage of the population over 16 that is unemployed but seeking work	9.667 (2.448) (4.4-17.5)
X7= Single parent households	Percent of children in households that are headed by single parent	36.614 (9.640) (13-74)
X8= Rural	Percentage of the population that is located in a rural setting (Binary 1= Rural over 50%)	64.6 (47.9) (0-1)
X9= Median Household Income	Median total income for the county	40,948.38 (7,318.494) (29,615-66,950)
X10= Not proficient in English	Percent of population not adept in the English language	2.348 (1.796) (0.1-12.4)
X11= Some College (%)	Percentage of population 25-44 with some secondary education. (Not necessarily graduates)	54.889 (9.156) (26.4-80.1)
X12= %<18	Percent of population below 18 years of age	22.057 (2.810) (13.2-30.1)
X13= % >65	Percent of population over 65 years of age	16.766 (4.248) (7.1-28.5)
X14= Female (%)	Percent of population that is female	50.587 (1.621) (43.6-53.7)
X15= Mountain	County located in Mountain region	0.23 (0.421) (0-1)
X16= Coastal	County located in Coastal region	0.41 (0.492) (0-1)

Mean
(Standard Deviation)
(Min-Max)

Fig. 2

Variable	Y1= Poor mental health days	Y2= Poor physical health days	Y3=Poor of fair health
X1= Physical Inactivity	0.073 (0.000)	0.067 (0.000)	0.382 (0.000)
X2= Adult Obesity	-0.035 (0.01)	-0.004 (0.705)	0.037 (0.609)
X3= Excess Drinking	0.029 (0.005)	0.005 (0.586)	-0.173 (0.002)
X4= Access to Exercise Opportunities	-0.003 (0.091)	-0.003 (0.024)	-0.000 (0.973)
X5= Limited Access to Healthy Foods	-0.011 (0.224)	-0.015 (0.049)	-0.117 (0.016)
X6= Unemployment	-0.036 (0.023)	-0.014 (0.310)	0.098 (0.246)
X7= Single Parent Households	-0.002 (0.756)	-0.005 (0.217)	0.022 (0.43)
X8= Rural	-0.138 (0.103)	0.141 (0.049)	0.711 (0.119)
X9= Median Household Income	0.000 (0.001)	-0.000 (0.010)	-0.000 (0.022)
X10= Not Proficient in English	-0.102 (0.000)	-0.078 (0.000)	0.567 (0.000)
X11= Some College	0.002 (0.815)	-0.003 (0.630)	-0.065 (0.062)
X12= %<18	0.025 (0.231)	0.017 (0.092)	0.02 (0.859)
X13= %>65	-0.017 (0.231)	-0.032 (0.006)	-0.197 (0.008)
X14= Female	0.01 (0.693)	0.029 (0.155)	-0.305 (0.019)
X15= Mountain	0.104 (0.373)	0.348 (0.000)	1.337 (0.099)
X16= Coastal	-0.385 (0.000)	-0.12 (0.077)	1.337 (0.002)
Sig F: Y1= 0.000 Y2= 0.000 Y3= 0.000			

Mean
p-value

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