

Determinants of Body-Mass Index in Adolescent Networks

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CHAPTER 1 - INTRODUCTION

Introduction to Health Disparities

Most residents of the United States want a society in which all people live long and healthy lives (CDC). At the core of public health lies this founding doctrine, that good health for all is something to be pursued through rigorous inquiry. In the words of Charles-Edward Amory Winslow, a seminal figure in public health, public health is “the science and art of preventing disease, prolonging life and promoting health through the organized efforts and informed choices of society, organizations, communities and individuals.” Public health is a unique science in that it has an end goal: a society in which every person is given the social and medical resources to live a long and healthy life.

The major obstacle to this end goal is the persistence of health disparities within every society. Health disparities are “differences in health outcomes between groups that reflect social inequalities” (CDC). Within the United States, the list of health disparities is extensive and saddening. One example of an area with large disparities in infant mortality rates, where infants born to black women are “1.5 to 3 times more likely to die than infants born to women of other races/ethnicities.” Another example is in tobacco use, where “smoking rates decline significantly with increasing income and educational attainment.” (CDC) A recent Healthy People 2010 Midcourse Review suggested that little progress has been made in the United States with respect to reducing disparities defined by “race/ethnicity, sex, education, income, geographic location, and disability status” (CDC).

Health disparities are a serious issue because they are often the result of flawed systems. It has been suggested that “bias, stereotyping, prejudice, and clinical uncertainty on the part of health care providers may contribute to racial and ethnic disparities in health care” (McConnell).

The policy implications of health disparities are extensive, and can involve “payment systems” “structured to ensure an adequate supply of services to minority patients” (Gordon-Larsen).

Research in public health attempts to inform policy makers so that they may be better equipped to meet the challenges associated with widening health disparities.

A Review of the Obesity Epidemic

The most pressing of health disparities at this time is the obesity epidemic. In the United States, “from 1976-1980 to 2007-2009, obesity prevalence increased from 15 to 34% among adults and from 5% to 17% among children and adolescents” (CDC). Obesity is a serious public health problem because it is associated with a number of health problems, including sleep apnea, psychological problems, gallbladder disease and hypertension. More importantly, obesity is a cause of decreased lifespan, due to diseases such as diabetes and cardiovascular disease. Indeed, obesity accounts for 300,000 premature deaths each year, second only to tobacco among preventable causes of death (Gordon-Larsen). The prevalence of obesity is so great that it now referred to as an epidemic across age, racial/ethnic and socioeconomic groups (Gordon-Larsen). Obesity becomes a nationwide problem because it requires divestment of resources in treatment. People who become sick due to obesity cannot work as efficiently, and are often less happy. Given the vast consequences of the obesity epidemic, we must treat it as a national priority.

In public health, “a good understanding of the determinants of health disparities is critical to help develop related interventions to eliminate health disparities” (Wang and Chen). With respect to almost all disparities, public health has come up with a core principle: socioeconomic status is a strong predictor – a *determinant* – of individual and community health. Regularly, public health studies uphold this principle as valid and important. Studies of the determinants of

obesity can be divided into three categories: direct effects studies, contextual effects studies and network studies. Direct effects refer to how a specific aspect of a person (his socioeconomic status, his income) is shown to affect his health. Contextual effects refer to how a person's context – his neighborhood or school, for example – is shown to affect his health. I will go on to suggest that these two effects provide us with an incomplete understanding of how BMI is affected. I will ultimately argue in this chapter that in addition to contextual effects and direct effects, *network effects* may provide a valuable understanding of how a person's social environment can be quantified and analyzed for its effect on health.

Direct Effects

Direct effects refer to how specific indicators about a person at the individual level, such as race, gender, age, income and education, can affect obesity. I will now discuss two studies that display the effectiveness of the direct effects model in obesity prediction. The first of these studied how socioeconomic status affects health of a nationally representative sample of adults. The second studied how socioeconomic status affects health of a nationally representative sample of children.

The USDA 1994-1996 Continuing Survey of Food Intakes by Individuals (CSFII)

The USDA CSFII is a multistratified and nationally representative sample that includes information on dietary information on 9,872 adults aged 20 years and older. Of these adults, 4,356 were under 65 years of age and had completed a Diet and Health Knowledge Survey, answering questions regarding awareness of a healthy diet and self-perception of weight status. This study surveyed the answers to five categories of questions: nutrition knowledge and beliefs

(NKB), consideration of key factors affecting food choices, awareness of nutrition-related health risks, overall nutrition and health-related psychosocial factors (NHRPF) score and intention to improve diet (Wang and Chen). The chief goal of this study was to analyze “whether and how much of the racial/ethnic differences in US adults’ dietary intakes, exercise and weight status may be explained by NHRPF and SES” (Wang and Chen). Variables controlled for included survey year, age, sex, region, degree of urbanization, chronic disease, and self-rated health. In my analysis in this thesis, I went on to use many of these controls for my own model, given their potential for affecting BMI. The dependent variables analyzed in this study included overall quality of diet, measured by the 2005 Health Eating Index (HEI) and weight status, measured by BMI. An overweight BMI was classified as 25 to 30, while an obese BMI was considered a BMI above 30. I found that these classifications of overweight and obese held for the majority of studies that analyzed the determinants of obesity.

This study found, ultimately, that the role of nutritional and health-related psychosocial factors (NHRPF) was not statistically significant in explaining ethnic differences in diet, exercise and obesity. However, socioeconomic status did play a much more important role. After controlling for socioeconomic status, the percentage change in HEI was 30% for non-Hispanic blacks versus whites, and the risk of overweight and obesity was changed by 38% after controlling for education and income. The study had a few important implications for my research, including that statement that the R-squared value showed that even with many variables included, the model could explain only a very small proportion (10 to 20%) of the variations in BMI and HEI. The authors pointed to the complex factors affecting such indicators as reasons for these low R-squared values. It is important to recognize the wide array of genetic and environmental factors that influence an individual’s BMI. Ultimately, this data points to the fact

that limited economic resources contribute to an increased risk of obesity. Hence, this study serves as an excellent example of the direct effects model.

The 1971-2002 National Health and Nutrition Examination Surveys (NHANES)

The NHANES survey is another national representative survey that includes data for 30,417 US children aged 2-18 years. A recent study chose to analyze the direct effect of SES on obesity with respect to children, in order to provide useful insights for developing effective obesity prevention and management programs and policies. This study defined at risk of overweight as greater than or equal to 85th percentile, and overweight BMI as greater than or equal to 95th percentile. The independent variable used to measure SES was the poverty income ratio, which is the ratio of household income and the poverty line published by the Census Bureau by family size. This poverty income ratio was divided into tertiles by socioeconomic group, which proved to be a better distribution than parental education. I would later take this into account in my research design, where I used education and control and income as the primary independent variable. This study was notable at the time because it considered the trend between SES and obesity in children and adolescents, which is rather understudied in current literature.

The results from this study suggested a reverse relationship between SES and BMI, only in white children and not in black children. Other interesting results included that black adolescent girls with a high SES were more likely to be overweight than their medium-SES counterparts (Wang and Zhang 20). Perhaps the most important result from this study is that it found an unparalleled increase in the prevalence of overweightness in American adolescents within the low and high SES groups. Also important is that the association between SES and

overweight has become weaker over the past three decades, while the prevalence of obesity has increased. For example, the prevalence of obesity went from 7.1%, 6.4% and 3.8% in low, medium and high-SES girls to 17.9%, 10.6% and 10.6%. This high increase in percent overweight points towards the urgency of solving the determinants of obesity. The lessening strength of the association, however, points towards the further weakness of the pure direct effects model in predicting BMI.

Contextual Effects

Contextual effects refer to how a person's context (his neighborhood, his school, etc.) affects his health. Along with direct effects, contextual effects are one of the two primary ways that determinants of obesity are studied in current literature. In this section I will discuss three recent studies that reviewed the role of contextual effects. The first looked at how the level of sprawl in metropolitan and rural areas in the United States affects exercise time and obesity. The second considered the role of walkable land uses and multi-family dwellings in obesity prevention. The third reviewed how the presence of recreation facilities can explain variations in child obesity levels between census blocks.

The 1998-2000 Behavioral Risk Factor Surveillance System (BRFSS)

The BRFSS is a population-based, random digit-dialed telephone survey administered to U.S. civilian non-institutionalized adults. A recent review suggests that this survey has moderate to high reliability for health behavior and health status variables. A 2003 study using BRFSS data emphasized that “74% of U.S. adults do not get enough physical activity to meet public health recommendations, and that one in four U.S. adults remains completely inactive during

their leisure time” (Ewing). The authors of this study hypothesized that residents of sprawling places would walk less, weigh more and have a higher prevalence of health problems linked to physical inactivity. The independent variable was a composite factor including several variables from Smart Growth America’s metropolitan sprawl index, which was used to represent urban form at the metropolitan level. A similar county sprawl index was created to match the metropolitan sprawl index. The dependent variables were categorized as any physical activity, recommended physical activity and minutes walked. A threshold of physical activity was established, with an emphasis on walking because of its “documented relationship to urban form and its dominance as a leisure time activity” (Ewing). The sample consisted of 206,992 respondents from counties and 175,609 from metropolitan areas, selected because they had known places of residence with urban sprawl indices.

The models used in this study were with Hierarchical Linear and Nonlinear Modeling Software. Results showed that residents of more compact counties were expected to have BMIs 0.17 kilograms per meter squared lower than residents of a more sprawling county. Ultimately, it was found that in counties, sprawl appears to have direct relationships with BMI and obesity. In metropolitan areas, it seems that sprawl appears to be associated similarly with minutes walked. Implications of this study suggest that those people living in sprawling counties tend to walk less in leisure time, weigh more, and have greater prevalence of hypertension than those living in more compact places. These results advocate for more compact development patterns, and advocate for incorporation of urban form into public health analysis. This particular study provides a good example of how urban sprawl is part of a contextual effects model and can act as a determinant of health.

Entropy Scores and BMI

There are other studies that have considered the relationship between physical environment and obesity. There has been a large amount of support in urban planning for mixed use, where diversity of walking environment is found to be associated with walking (Brown). A recent groundbreaking study considered industrial land uses, which have not been incorporated into studies of land use and BMI. The authors of this study used entropy scores, which characterize the equality of distribution of designated land uses. The sample used in this study was 5000 randomly chosen licensed drivers between the ages of 25 and 64 in Salt Lake County, Utah. An overweight BMI was defined to be between 25 and 29.9 while an obese BMI was greater than 30.

The authors found that having more educational institutional or office space was correlated with lower risks of being overweight. Results also suggested that the mixture of land uses was not as important as just the presence of walkable land uses. Much like the study above done with BRFSS data, this study found that multi-family dwellings with greater density were shown to be associated with lower BMIs and more exercise. This provides interesting implications for policy, as it is typically very controversial to add multi-family dwellings to communities (Brown). Other interesting implications of this study included that rail stop users can “accrue 8.3 minutes of walking per day walking to transit, which over time may prevent weight gain and prevented estimated expenditures of \$5500 per person in additional health costs” (Brown). This study suggested the value of the contextual effects model as a way of understanding the determinants of obesity.

The National Longitudinal Study on Adolescent Health

This survey is the same one that I used in my research, so it will be discussed at length in the next chapter. Briefly, Add Health is a longitudinal, nationally representative school-based study of US adolescents in grades 7 through 12. A recent study used Add Health data to analyze the importance of neighborhood-level SES, measured by access to community recreational facilities. This study pointed to the lack of population-level analyses of the relationship between SES and recreational facilities. The authors of this study drew a 5-mile buffer around each respondent (N=20,745), using this buffer to develop census-block groups that could be analyzed for the presence of recreational facilities. Given the empirical connection between education and health outcomes, the authors used education level of the census-block group as the primary indicator of SES. The Physical Activity (PA) and recreational facilities analyzed included schools, public facilities, youth organizations, parks, YMCA, public fee facilities, instruction-based facilities, outdoor and member facilities (Gordon-Larsen).

Results of this project showed that for every 100% increase in the proportion of individuals in a census block group with college or greater education, there was a greater than twofold increase in access to facilities. This suggests a clear connection between education and the presence of exercise facilities. It was also found that ethnic minorities and those of lower education are at highest risk for lack of PA and recreational facilities. With respect to the original contextual effects in question, this study found that the relative odds of overweight decreased as the number of recreational facilities increased. Thus, this study provided clear support for the contextual effects model as a statistically significant explanation of weight differences.

The Combination of Direct and Contextual Effects

Some studies have pointed towards more comprehensive models that take into account both direct and contextual effects. This sort of cumulative model is the direction that I ultimately took with my thesis research. A recent study using Add Health Data discussed how aspects of the built environment and aggregate indices of SES were unlikely to appear in isolation in neighborhoods (Nelson). The purposes of this study were to identify meaningful patterns in neighborhood environments that could determine PA and to describe the associations between these patterns and adolescent residents' PA and weight status. The independent variables included residential location, buffers for respondent locations, physical activity facilities within 3 km, walkability within 3 km, road type within 3 km, census measures and crime. The dependent variable was BMI, with 95th percentile used to classify overweight.

The results of this study showed generally that traditional measures of neighborhood characteristics such as median household income “may not capture the complexity needed to understand how environment affects behavior” (Nelson). Results contradicted previous studies, such as the aforementioned one on sprawl and obesity. This study found that there were actually beneficial associations between living in a suburban area and being of a healthy weight. Generally, the results of this study did support previous findings that low-income, racial/ethnic minority, and rural populations are less physically active and more overweight and obese. Policy recommendations from this study included the development of effective population-wide health promotion strategies that can address pre-existing neighborhood with a set of existing characteristics that determine health outcomes. Ultimately, this study serves as a good example of how direct and contextual effects can be combined to provide a unique framework from which to understand the determinants of obesity.

Resilience: A Shortcoming of the Pure Direct Effects and Contextual Effects Models

It was during this research of direct effects and contextual effects models that I found a study discussing resilience. Resilience is the phenomenon by which individuals defy the BMI trends that would be expected based on direct and contextual measures of SES. This study used data from the Resilience for Eating and Activity Despite Inequality (READI) study, which analyzed a sample of 3235 women aged 18-45 years from 80 urban and rural neighborhoods throughout Victoria, Australia. The independent variable used in this study was the Socioeconomic Index for Areas (SEIFA Index of Disadvantage), which incorporates factors such as neighborhood income and proportion of the neighborhood employed. An overweight BMI was defined to be from 25.0 to 29.9, while an obese BMI was 30.0 or higher. Other correlates used included behavioral factors, dietary intake, intrapersonal, social and physical environmental factors and sociodemographic factors.

This study found that “women classified as ‘resilient’ to obesity tended to be younger, born overseas, more highly educated, unmarried and to have higher or undisclosed household incomes” (Ball). It is here that my research question really begins to take root, as I was curious to understand more about resilience. It seemed to me that resilience pointed towards a shortcoming in the pure direct effects and contextual effects models. There could be a social phenomenon underlying the ability of some women to be overweight-resistant.

Another recent study with a similar conclusion analyzed data from the Los Angeles Neighborhood Services and Characteristics Database and decennial census. In this study, the author tested whether collective efficacy, “a neighborhood-level measure comprised of aggregated responses to items that capture trust, cohesion and the willingness to intervene for the common good among residents,” could explain why local income inequality is associated with

increased likelihood of obesity. The models used were logistic regressions of individuals within neighborhoods. The dependent variable used was BMI, with obesity defined as a BMI over 30.

The authors of this study found that “collective efficacy exerts an independent and beneficial effect” on obesity levels (Bjornstrom). It was also found that “economically heterogeneous neighborhoods contain characteristics that promote health” (Bjornstrom). This study also advocated for a comprehensive understanding of obesity that considers the role of social resources in determining health. The research pointed ultimately towards policy programs that increase collective efficacy in neighborhoods as a means of promoting good health.

Both of these studies hint at a new paradigm for public health research, one that considers social connections in place of social environment. This idea was encapsulated in a landmark study published in the *New England Journal of Medicine* in 2007. This study analyzed “a densely interconnected social network of 12,067 people assessed repeatedly from 1971 to 2003 as part of the Framingham Heart Study” (Christakis and Fowler). The authors found that “a persons’ chances of becoming obese increased by 57% if he or she had a friend who became obese in a given interval” (Christakis and Fowler). These results suggest that obesity spreads through social networks, suggesting that social status – in a way that is different from traditional models of socioeconomic status – is also an important health determinant (Christakis and Fowler). Social status in the network sense has to do with a person’s friendships and ties to other people. My research thus took a new direction, as I tried to understand the role of networks and how they fit in the discussion of direct and contextual effects models. I will now discuss further studies that have analyzed the network and structural models of obesity.

Network/Structural Effects

A recent study used data from in-school surveys with “11-15-year old adolescents in four schools in the greater Los Angeles area” (Valente). This sample included 562 respondents who provided the full data needed for analysis. The purpose of this study was to study the “likelihood of being overweight as a function of demographic characteristics, attitude self-reports, network properties and friends’ weight status” (Valente). The authors of this study used multilevel regression as a model for analysis. The rationale behind this analysis was that adolescent friend groups often form around shared behaviors that can indirectly and directly affect weight status.

Results ultimately showed that overweight adolescents were more likely to have overweight friends than normal peers, and that overweight adolescents were also less likely to be named as friends than normal weight adolescents. This is worrisome, as it suggests that overweight girls are being socially marginalized, which could lead to further deleterious behaviors. Compared to nonoverweight girls, overweight girls had an approximately twofold increase in friends’ average BMI percentile. This study was relevant to my research because it pointed towards the social network definition of environment as something that is not necessarily physical, but rather as a social environment in which health behaviors can be transferred.

Another study considered the presence of obesity related behaviors in friendship networks (de la Haye). These authors refer to how “as adolescents spend increasing time with friends, the potential for the norms and behaviors of peers to be influential is increased” (de la Haye). This study used Exponential Random Graph Models (ERGMs) to model the structure of complex social networks. The chief aim of the study was to determine if close adolescent friends display a similarity in obesity-related behaviors. Data was collected from male and female students from two independent middle schools in a major Australian study.

Results from this study showed that adolescent school friends were similar in certain behaviors, specifically with regard to leisure time activities. In high-calorie food consumption, male friends in two of the networks were alike in how they consumed snack foods and fast food. Popularity also seemed to be associated with some obesity-related behaviors, a point that became relevant after I had finished my analysis. In my research I would go on to consider people with ties at one, two and three degrees of separation. It is possible that people who have friends at three degrees of separation will be more popular and hence be more likely to have higher BMIs. Ultimately, this paper suggested that similarity in leisure activities and food consumption behaviors between friends may explain the social contagion effect of overweight and obesity. This is a difficult claim to make, however, given the strong nature of the contextual effect due to neighborhood.

The Beginnings of a Research Design

I have now completed a thorough discussion of direct, contextual and network effects, with a clear consideration of the shortcomings and benefits of each of these models. I dissected important studies in the field of direct effects, which have become a staple of public health research over the past three decades. The direct effects models are useful and provide statistically significant explanations of BMI, but the strength of the association is decreasing over time. I also analyzed contextual effects models, which consider the role of one's neighborhood or community in one's health. I explained that contextual effects models are quite good. I then moved on to cover a few rare studies that have combined network and contextual effects. Even these studies still cannot account for certain phenomena, such as resilience. Studies of resilience pointed towards the newest of the three areas: network effects. Studies have shown that obese

adolescents seem to affect their peers in a statistically significant manner, suggesting that obesity can spread like a contagious disease.

I noticed, however, that there is more room to study networks and their effect on obesity. After thinking extensively of the direct, contextual and network models, I thought of bringing socioeconomic status, a staple of direct effects research, to the network model. Such research seemed to be missing from the current discussion of income and obesity. Given this new, uncharted area in the research, I began formulating an interesting research question. The specifics of this question will be discussed in Chapter 3 of this thesis.

Figure 1 – Prevalence of obesity among boys. Source: CDC

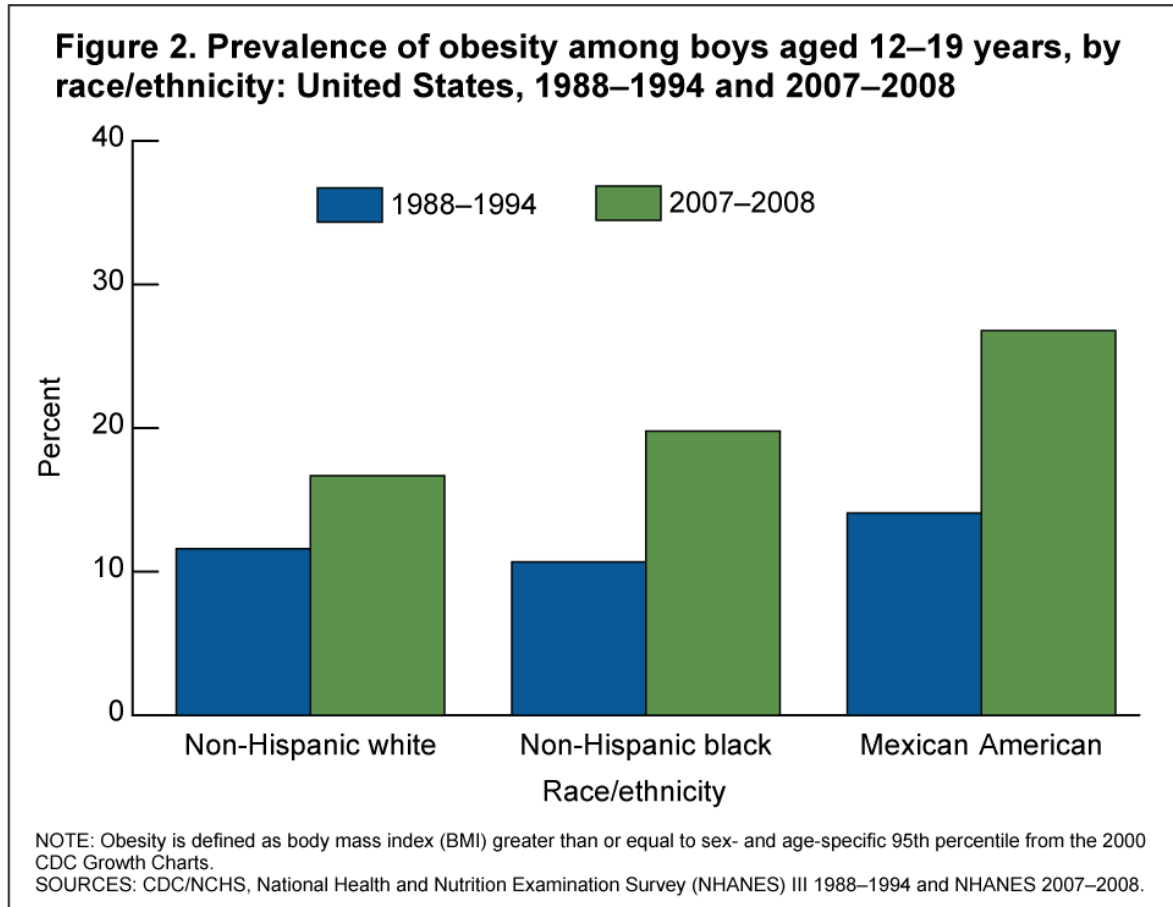


Figure 2 – Percent obese in America. Source: CDC

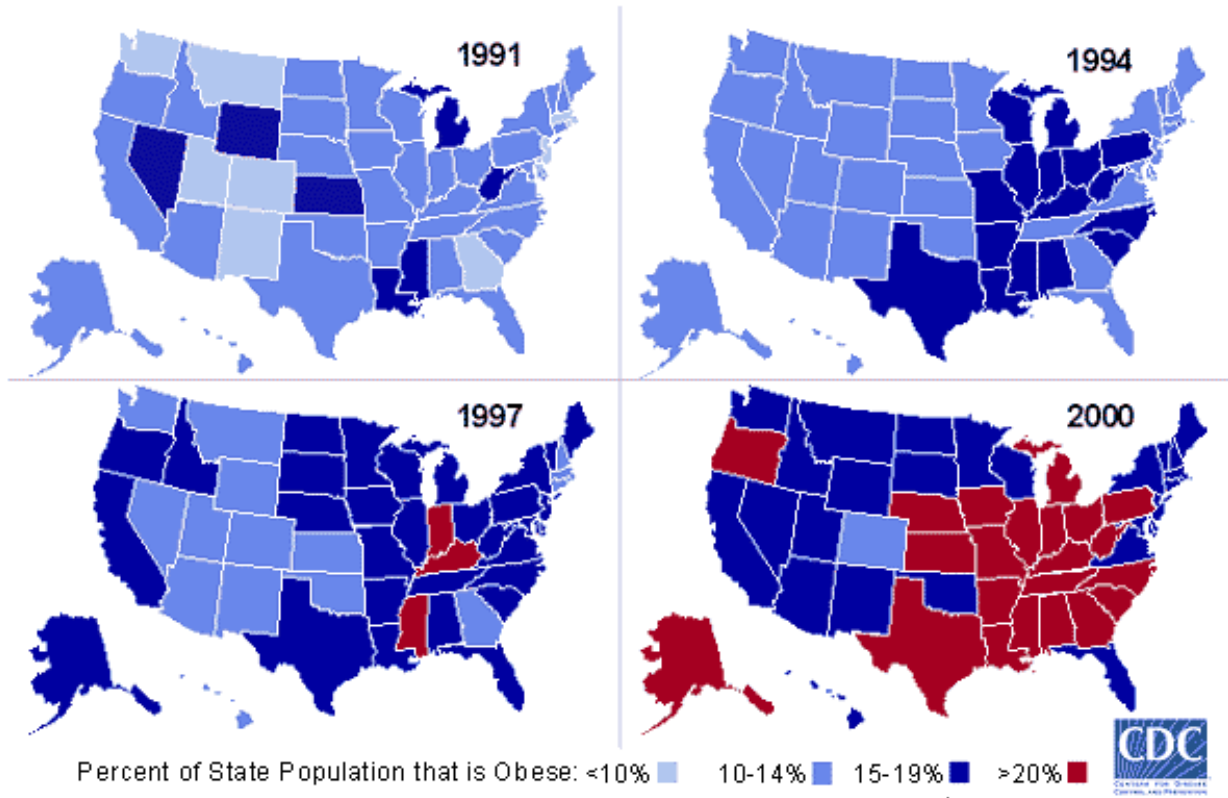
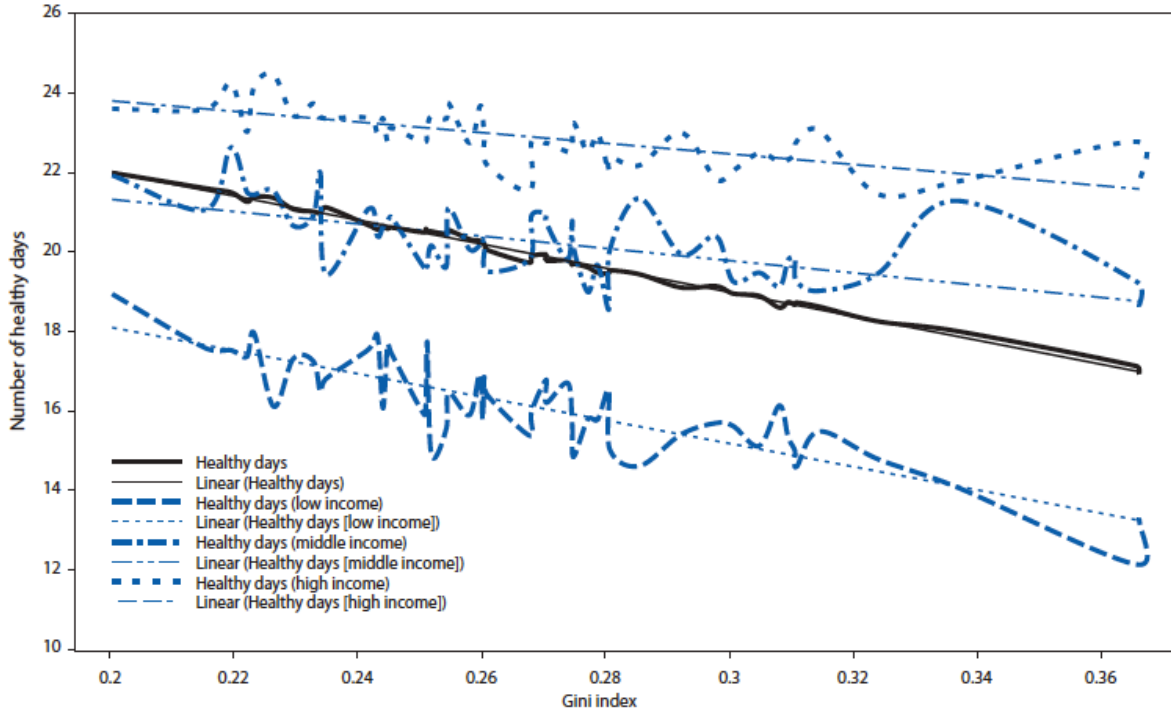


Figure 6: Obesity Trends Among U.S. Adults, BRFSS¹

Figure 3 – Relationship between income group and average number of health days. Source: CDC

FIGURE 5. Gini Index and average number of healthy days, by Income group — United States, 2007.



Source: Gini index and average number of healthy days was estimated by using data retrieved from the Behavioral Risk Factor Surveillance System, 2007. Available at <http://www.cdc.gov/BRFSS/>.

CHAPTER 2 – AN INTRODUCTION TO NETWORK THEORY

Network Theory: an Introduction

In this chapter, I discuss some of the basic aspects of network theory. Many of these principles were not used directly in my research, but they provided me with a mental framework from which to approach my question and the applications of my findings. Readers with a basic understanding of network theory can skim over this chapter.

Succinctly defined, a network is “a pattern of interconnections among a set of things” (Easley). Humans inhabit social networks, which have grown enormously in complexity with technological advances that allow for a wider variety in strength and diversity of connections with other human beings. Even the information processed by humans has a networked structure. “These structures too have grown in complexity, as a landscape with a few purveyors of high-quality information publishers, news organizations, the academy has become crowded with an array of information sources of wildly varying perspectives, reliabilities, and motivating intentions” (Easley and Kleinberg). “Understanding any one piece of information in this environment depends on understanding the way it is endorsed by and refers to other pieces of information within a large network of links.” Generally speaking, network phenomena are visible everywhere. People are “connected by e-mail exchanges, financial institutions are connected by borrower-lender relationships, and blogs are connected via links from one to the other” (Easley and Kleinberg).

My analysis in this thesis uses core components of network theory. Networks are defined by two specific components. The first of these is a node. In the case of a social network, a node refers to a person. An edge is a connection between two nodes, and in the case of a social network represents a friendship or acquaintance of some sort. Given these characteristics, the

basic definition of a social network is “an organized set of people that consists of human beings and the connections between them” (Christakis and Fowler).

Figure 4, located at the end of this chapter, provides an example of a network graph. Each node refers to a member of a 34-person karate club, and persons 1 and 34 are considered the most central because they have the highest level of connection to the network. In studies of clinical interventions targeting obesity reduction, the most central nodes are considered to be of particular importance because they can have the greatest influence on the network. These nodes are considered to have the highest *degree*, or number of links, to other nodes. My analysis for this thesis ultimately omitted a study of the degree number of individuals, but this type of analysis is important and will be useful in future steps with my research question.

In social network theory, the term *ego* is used to refer to the person whose behavior is being analyzed, while *alter* refers to a person connected to the ego who may influence the behavior of the ego. Ego-alter connections are directed. They can be one-way, if the ego names the alter and the alter does not name the ego back, or they can be *mutual*, where the ego and alter name one another as friends. This distinction between mutual and one-way relationships is particularly important when considering how health behaviors are passed within networks. Recent research suggests that mutual ties are most important in the spread of sleep loss and drug use in adolescent social networks (Fowler). My research, due to come constraints, considered chiefly mutual connections between adolescents.

Networks have various interesting characteristics. One of these is that networks tend to “amplify the success of products and technologies that are already doing well” (Easley). This amplification, part of a larger set of phenomena referred to as *network effects*, is evident through YouTube, which by definition had an added value once it became the most popular video-

sharing site. There can also be cascading effects, “in which a new behavior starts with a small set of initial adopters and then spreads radially outward through the network” (Easley and Kleinberg). Sometimes, this sort of cascading behavior is called social contagion “because it spreads from one person to another in the style of a biological epidemic” (Easley and Kleinberg). A good example of such cascading behavior is evident from a recent publication on prescribing behavior among networks of doctors, which found that prescribing behavior spreads through networks through cascading behavior (Christakis and Fowler). Amplification and cascading are crucial to my research because they suggest that interventions built on the network model could be highly effective. Good health behaviors can become contagious, spreading like wildfire through a network.

An explanation for this contagion lies in the phenomenon of *triadic closure*, which refers to “if two people in a social network have a friend in common, then there is an increased likelihood that they will become friends themselves at some point in the future” (Kleinberg). This is closely related to the concept of the clustering coefficient, which is defined for a given node as “the probability that two randomly selected friends of that node are friends with each other” (Kleinberg). “The more strongly the process of triadic closure operates in the neighborhood of the node, the higher the clustering coefficient will tend to be.” Thus, triadic closure explains contagion because a behavior can travel between two people, and if one person is friends separately with each of them, then that person may in the future cause the two friends to become friends with one another. In this way, behaviors are transferred through the triad.

These ideas are valuable because they suggest the immense value of social connections in determining behavior. Given the impact that social connections have on individuals, public health researchers can approach health interventions from a completely novel standpoint.

Network theory empowers researchers to consider how to change a person's *social* environment, rather than his physical environment. This distinction provides the bases for interventions that involve changes in network structure and the distribution of social connections between people. In the final chapter of this thesis, I will discuss these findings extensively.

Conclusion

Network theory provides a completely unique perspective from which to approach problems in public health. In social networks, behaviors are transferred from person to person. This is such a unique idea for public health because it challenges the notion that people are affected only by factors associated with their physical environment, such as having a poor neighborhood or a poor school. I chose to study network effects in this thesis because network theory may explain certain shortcomings in current models of health determinants. Perhaps social connections explain much of the variations in adolescents' weight, especially given the substantial influence of peers during this age.

Figure 4 – The social network of a 34-person karate club. Source: Wasserman

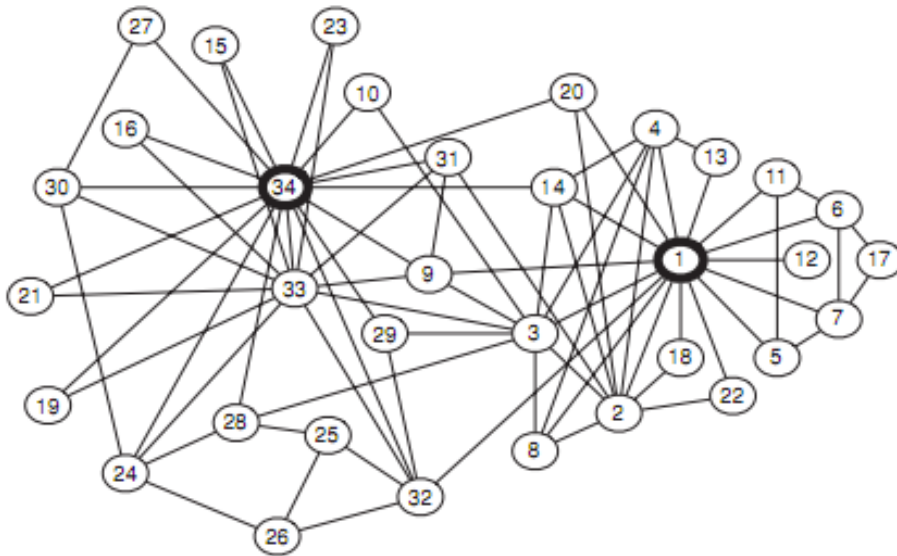


Figure 1.1. The social network of friendships within a 34-person karate club [421]. (Drawing from the *Journal of Anthropological Research*.)

Figure 5 – A network displaying the spread of an epidemic disease, a form of cascading effects. Source: Wasserman



Figure 1.12. The spread of an epidemic disease (such as the tuberculosis outbreak shown here) is another form of cascading behavior in a network. The similarities and contrasts between biological and social contagion lead to interesting research questions. (Image from the American Public Health Association; [16].)

CHAPTER 3 – RESEARCH DESIGN

In this chapter, I begin with a discussion of my data source, the National Longitudinal Study of Adolescent Health. I then explain why it is crucial to study obesity among adolescents. I conclude with a description of my research design, in which I explain my research question, hypothesis, and variables.

Add Health Data

In my research, I analyzed data from the National Longitudinal Study of Adolescent Health (abbreviated Add Health). Add Health is the only nationally representative study of adolescent health. The data for Add Health was collected through a combination of surveys and in-home interviews. It includes four waves; Wave I being data collected through in-school surveys from 1994-1995 (Udry). Wave II data was collected approximately one year later, through in-home interviews of youth and a principal caregiver, who was typically the mother. Wave III data was collected from 2001-2002, in order to study the transition from adolescence to adulthood. Wave IV data, collected 6 years after Wave III, is less useful for my purposes because it contains hardly any network data.

For the purposes of my project, Add Health surveys and interviews contain several useful variables, including gender, weight and height (which can be used to calculate BMI), family's income and neighborhood average income. Most importantly, the Add Health data includes dyad files, which record the individuals (*alters*) that were named as friends by the subjects (*egos*).

The Importance of Obesity Among Adolescents

Given that I used data on adolescents in my research, I will discuss here some reasons for why it is important to study obesity in adolescent populations. First, “social network analyses have revealed that overweight adolescents are less central to their social networks and have fewer friendships ties than average weight adolescents” (Xie). This is important because it suggests that in addition to suffering from poor health, obese children are socially marginalized. Another example of the consequences of obesity in children is a 2005 study that analyzed the relationship between BMI and psychological correlates in Chinese school children during the period of economic transition. Two important measured used in this study were perceived peer isolation (PPI) and perceived availability of social support (PASS). This study found that there was a “significant association between BMI and depressive symptoms” (Xie). This finding is particularly important, and contributes to the urgency with which we must come up with innovative solutions to obesity. In girls, the effect of BMI on depressive symptoms is even higher, given a link in girls between higher BMI and greater PPI. However, this relationship is absent for high PASS girls. Independent of the beneficial effect of social support, it stands that obese children are more likely to be depressed. These findings are shown to have dire consequences, given follow-up studies of patients who were obese as adolescents who ultimately showed lower education levels, lower incidence of marriage, lower household incomes and higher rates of poverty. Studying obesity among adolescents is important, and thus the add health data proved to be particularly valuable. I will now discuss my research design, and then move on to the next chapter, where I outline my results.

Research Design

I used the open-source R software environment to carry out my analysis. My research design was based on the availability of data on 14,738 individuals in Wave II of the Add Health data set.

Question

Does friends' average income at one, two and three degrees of separation have a significant impact on ego BMI?

Hypothesis

Higher average income for friends will have a beneficial or inverse relationship with BMI. The magnitude of this effect will decrease from one to two to three degrees of separation. The direct effects and contextual effects included as control variables in the model will have statistically significant implications for BMI.

Dependent Variable

My dependent variable was body-mass index (BMI), measured by weight in kilograms divided by height in meters squared.

Independent Variables

Independent variables: Friends' family income at 1 degree of separation, friends' family income at 2 degrees of separation, friends' family income at three degrees of separation.

Control Variables

I chose control variables that could be providing alternate explanations for BMI. The first of these was ego family income, chosen because family income is representative of the direct effects models discussed in chapter one of this thesis. As I discussed extensively in chapter 1, much literature has shown that a person's income is inversely associated with his BMI.

I chose to control for ego age because this is a sample of adolescents. Age is particularly important because body type changes significantly during adolescence. By controlling for age, I was able to avoid an explanation for BMI that could be associated with changing body type or physical development. I used an age squared term as well.

I controlled for ego gender because females have a lower BMI than males do. This would have affected my results.

I controlled for ego race/ethnicity because race is regularly shown to be a strong predictor of BMI. Blacks and Hispanics tend to have higher BMI values, while Asians tend to have lower BMIs.

I controlled for school average income because the contextual effects models suggests that one's environment has a strong influence on one's BMI. By including this in the model, I was able to parse out the social influence from the influence of the physical environment. This was a way of controlling for the contextual effects discussed extensively in chapter 1.

I controlled for ego mother's education because mother's education is shown to be inversely associated with BMI.

Model and Coding for Variables

Model and specifications

In keeping with the majority of literature on socioeconomic status and BMI, I used a linear model in the ordinary least squares regression form to test my hypothesis. I treated all connections between people as mutual. In other words, if one person named a friend but that friend did not name him back, that connection was treated the same as a mutual one.

I used data only from the second wave of Add Health data. At Wave III and Wave IV, I expected that the effect of high school friends would be mitigated due to changes in friend network structure after high school. Put more simply, few people retain strong links to high school friends after they have passed the age of twenty.

Coding for Variables

I used the programming language R, an open-source software environment that is used widely for network analyses. I coded for BMI as kilograms of weight divided by the square of height in meters. Mother's education, race and gender were already included in Add Health codebooks, so they simply had to be specified for Wave II. Average income for each school had to be coded for.

I also had to code for friends average income at each degree of separation. This was done by first turning the add health friendship data into an edgelist of undirected connections between people in the sample. This edgelist was indexed by school, and by using a paths function I could develop matrices for each school, where the individual entries were the average friends' income for each person in the dataset. This was completed for friends at one, two and three degrees of separation.

Using Amelia and Zelig

Although not planned for initially, I eventually used the programs Amelia and Zelig to account for the large amounts of missing data in the Add Health Wave II network model. Amelia is a program for missing data that uses a particularly effective version of the multiple imputation software. The purpose of multiple imputation is to replace missing data in such a way that it continues to reflect relationships in the data while accounting for the uncertainty in this replacement. Amelia is better than other methods of dealing with missing data, “including listwise deletion, mean substitution and single imputation, which are often biased and inefficient” (King). Amelia was also particularly useful because it does not crash as often as other similar programs.

Zelig was used in conjunction with Amelia to interpret the results of multiple imputation. Zelig generalizes the Clarify program for Stata, and allows one to combine multiply imputed data sets to deal with missing data. In my analyses, I use the least squares regression model in Zelig.

CHAPTER 4: RESULTS AND ANALYSIS

In this chapter, I start with a look at some of the raw data from the Add Health study. I consider the strength of the control variables in my study. I explain how I confirmed usage of a linear model for the relationship between income and BMI. I then used significance tests to explain my findings on the relationship between friends' income and BMI. The reader may skip over the raw data and review page 6 of this chapter to see the ultimate answer to the question posed in the hypothesis. The figures referenced are included at the very end of the chapter.

Control Variables

Table 1 – The Effect of Control Variables

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	13.23050	4.983607	2.655	0.007948	**
Schoolaveinc	-0.013477	0.002198	-6.132	9.04e-10	***
Age	0.966076	0.603973	1.600	0.109735	
Agesq	-0.016264	0.018193	-0.894	0.371360	
Gender	-0.668437	0.093989	-7.112	1.23e-12	***
Hispanic	0.459181	0.142066	3.232	0.001233	**
Asian	-0.764607	0.201737	-3.790	0.000151	***
Black	0.868551	0.122905	7.067	1.69e-12	***
Mother_Educ	-0.078548	0.021717	-3.617	0.000300	***

 Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4.605 on 9683 degrees of freedom
 (1602 observations deleted due to missingness)
 Multiple R-squared: 0.04456, Adjusted R-squared: 0.04378
 F-statistic: 56.46 on 8 and 9683 DF, p-value: < 2.2e-16

Table 1 displays the roles of my various control variables. All the control variables I used, except for the age and age squared variables, had a statistically significant effect on BMI. Age was positively correlated with BMI but was not significant, and gender was negatively correlated (females have lower BMIs on average). Hispanics and blacks tend to have higher BMIs while Asians tend to have lower BMIs. Mother's education is inversely associated with

BMI. Most notable were school average income and the binary variable for whether or not the respondent was black. It seems that school average income has a mildly strong but highly significant effect on ego BMI, where a higher school average income by 10,000 dollars is associated with a 0.2 kilogram per meter squared decrease in BMI. Being black is associated with a nearly 1 kilogram per meter squared increase in BMI. After recognizing the high significance of school average income, I proceeded to plot ego BMI on school average income, to study the relationship between these variables more closely.

Table 2 – Friends at 1, 2 and 3 Degrees Income and Ego BMI

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	34.082223	25.661756	1.328	0.18485
Schoolaveinc	-0.030423	0.011018	-2.761	0.00601 **
Age	-1.339844	3.150750	-0.425	0.67087
Agesq	0.054847	0.096501	0.568	0.57009
Gender	-1.232773	0.460876	-2.675	0.00777 **
Hispanic	0.497007	0.770659	0.645	0.51934
Asian	-0.617360	1.092472	-0.565	0.57230
Black	1.556555	0.620364	2.509	0.01248 *
Mother Educ	-0.176425	0.108342	-1.628	0.10419
Own Incom	0.004270	0.002459	1.737	0.08317 .
Friends1Inc	-0.011524	0.011004	-1.047	0.29561
Friends2Inc	-0.002974	0.010707	-0.278	0.78132
Friends3Inc	-0.003397	0.009289	-0.366	0.71479

 Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
 Residual standard error: 4.679 on 422 degrees of freedom
 (10859 observations deleted due to missingness)
 Multiple R-squared: 0.1063, Adjusted R-squared: 0.08085
 F-statistic: 4.181 on 12 and 422 DF, p-value: 3.171e-06

Figure 1 – School Average Income and BMI (see end of chapter)

This scatter plot displays the strength of the relationship between school average income and BMI. It seems that there is an inverse relationship, where an increase in school average income is associated with a decrease in ego BMI. The majority of the school average income

values fall between 20,000 and 80,000 dollars. This is an important graph because it displays the contextual effect of school income on ego BMI.

Family Income and BMI

Figure 2 - Family Income and BMI (see end of chapter)

This scatter plot suggests no clear model for the relationship between family's income and BMI. The graph does show that the majority of the income values are clustered between 0 and 100,000 dollars, while BMI is in a range of 15-40 kilograms per meter squared. Given that an overweight BMI is classified as over 25 and an obese BMI is classified as over 29.9, a significant portion of the sample seems to be overweight and/or obese. Because there was such variation in the relationship between family income and BMI, I decided that a linear model would be the most effective way to visualize the data. This was also in line with the majority of public health studies on income and obesity, which have used linear models. The slight downward trend shown by the fitted line suggests the possibility of an inverse relationship between family income and BMI, where richer families tend to have children who are less overweight.

In Table 2, we can see there the effect of family's income on BMI is statistically insignificant. I found this interesting, and decided to re-run the model without including school average income, to see if the school effect was hiding the direct effect of family's income.

I found that mother's income does have an effect on ego BMI when school average income is not included in the model ($p=0.00264$). A \$100,000 increase in family's income was associated with a 0.3 decrease in BMI. This is a very small effect, and suggests that the contextual effect of school average income was much more significant in determining BMI. I

postulate that the strength of the contextual effect is increased by the fact that the contextual effect suffered from no missingness. All of the adolescents had values for average school income, while 2789 adolescents did not have data for family's income. The lower n-value for family's income would have reduced the significance of this value. Another reason for this is more obvious and has less to do with the data: the school average income gives more information than an adolescents' family's income. School income provides information about the facilities available for exercise, such as playgrounds and safe neighborhoods to walk in. Hence, it seems intuitive that school average income would have a greater effect on ego BMI. Noting the strength of school average income, I continued to study the question posed my hypothesis: how does friends' income affect BMI?

Friends at 1 Degree Income and BMI

Figure 3 – Friends at 1 Degree Income and BMI (see end of chapter)

This scatter plot displays again the immense variation in the relationship between income and BMI. I should note here that such a result is to be expected, given the incredible number of factors that affect BMI. It seems that the relationship between friends' income and BMI has no clear direction. Again, the ranges for BMI and income are approximately the same. Given the variation in this data, I expected the effect of friends' income to be very small and statistically insignificant.

As shown in Table 2, friends income at 1 degree had a negative but statistically insignificant impact on ego BMI ($p=0.29561$). It is important to note the high number of observations deleted due to missingness – there were 5,787 people missing the values necessary, meaning an additional 3,004 adolescents were removed to the model because they did not have a

value for friends at one degree of separation. The school average income remained a highly significant variable, and family's income remained statistically insignificant.

Friends at 2 Degrees Income and BMI

Figure 4 – Friends at 2 Degrees Income and BMI (see end of chapter)

This figure suggests the presence of a weak inverse relationship between the income of friends at 2 degrees and BMI. This is interesting, given that friends at 1 degree did not have a statistically significant impact on ego BMI. Nevertheless, the relationship here suggests that as friends at 2 degrees income increases, ego BMI decreases.

Immediately noticeable in Table 2 is that the number of observations deleted due to missingness increased dramatically at two degrees of separation. Although friends' income at two degrees remained inversely correlated with ego BMI, this result was not significant ($p=0.362$). I proceeded to look at friends at 3 degrees of separation and BMI.

Friends at 3 Degrees Income and BMI

Figure 5 – Friends at 3 Degrees Income and Ego BMI (see end of chapter)

In this figure, it is immediately noticeable that the number of data points drops significantly, suggesting that few adolescents have values for average income of friends at 3 degrees of separation. This drop-off in the n-value would make this relationship statistically significant. However, there does seem to be an inverse relationship between friends at three degrees income and ego BMI.

From Table 2, like one and two degrees of separation, the friends' income at three degrees of separation was associated with a decrease in BMI. This decrease was both small in magnitude and was statistically insignificant ($p=0.71479$). I understood that the lack of significance in friends' income could be explained in part by the high missingness in the data, so I looked into statistical methods to solve this problem.

Use of Multiple Imputation

Amelia and Zelig

I learned of Amelia, a program that uses multiple imputation to replace missing data and discover relationships that are hidden due to high missingness. I also learned of Zelig, which allows one to run models on imputed data. I ran multiple imputations with the data set I had been using above with linear models. I confirmed that the adolescent's family's income became statistically significant when the school average income was removed, suggesting again that the school average income has a stronger effect that overshadows the effect of family's income.

Table 3 – Imputed Data for Friends at 1, 2, 3 Degrees and BMI

	Value	Std. Error	t-stat	p-value
(Intercept)	11.776809059	4.815186228	2.445764	1.496749e-02
Schoolaveinc	-0.010068747	0.002216961	-4.541689	6.304847e-06
Mother_Educ	-0.070839326	0.026150215	-2.708939	1.171492e-02
Black	0.840471932	0.115747557	7.261250	7.363533e-13
Asian	-0.568796376	0.171152170	-3.323337	8.919956e-04
Hispanic	0.403713521	0.138658766	2.911561	3.828740e-03
Gender	-0.663617555	0.093284993	-7.113873	1.012769e-11
Age	1.141415149	0.584585643	1.952520	5.180744e-02
Agesq	-0.020540988	0.017541203	-1.171014	2.424754e-01
Own Income	-0.001514054	0.001029433	-1.470766	1.471969e-01
Friends1Inc	-0.002456568	0.001578909	-1.555864	1.350791e-01
Friends2Inc	-0.003369460	0.001389369	-2.425173	2.389571e-02
Friends3Inc	-0.005476535	0.005101530	-1.073509	3.348300e-01

I used the Amelia imputations to test the role of friends' income at one degree of separation. The p-value did decrease to 0.096 after imputation. However, it remained insignificant. The strength of the effect remained approximately the same, with a 100,000 dollar increase in friends' average income being associated with a 0.2 kilograms per meter squared decrease in BMI. I went on to consider the role of friends' income at 2 degrees of separation. The results show that friends' income at two degrees of separation had a small but statistically significant impact on ego BMI. This is an interesting result, and will be worth mentioning later in this paper. I finally looked at friends' income at 3 degrees of separation. Again, the p-value dropped to 0.334 but remained insignificant.

I will now discuss some further thoughts regarding the results from this table. The school average income variable was very significant, even at the $p=0$ level, and suggests that a \$10,000 increase in school average income would be associated with a 1 point decrease in BMI. This is a serious decrease, and for a child at the border between normal weight and overweight, this could mean the difference between good and bad health.

For the other control variables, all of them except for age proved to be statistically significant. A one point increase in mother's education (from high school diploma to technical training certificate, for example) was associated with a 0.01 kilograms per meter squared decrease in BMI. This makes sense given the wealth of literature that suggests that more educated people tend to have lower BMIs. The results for blacks and Hispanics makes sense, as those ethnic groups are known to have higher prevalence of obesity. Particularly noticeable is that being black increased one's BMI by almost a point. This result points towards the disparity in health across ethnic groups. In contrast, being Asian dropped one's BMI by approximately 0.5

kilograms per meter squared, providing further evidence of the racial/ethnic disparities in obesity prevalence.

Regarding my initial question, it seems that friends may have some influence on ego BMI. This effect is only significant at two degrees of separation, an interesting result that will require more substantial research. The network effects were smaller than the direct effects and contextual effects, suggesting that these models are very important in approaching the question of what determines obesity.

My analyses showed the repeated importance of the school average income as a determinant of obesity. Adolescents living in richer schools were much more likely to have low BMI values, and adolescents from wealthier families were also likely to have lower BMI values. Ultimately, I confirmed the direct effects and contextual effects approaches. The network question must be analyzed more thoroughly to see if there is a statistically significant effect of friends on ego BMI.

Further Steps

With respect to my analyses, there are more steps I can take to develop this research. I can repeat this analysis with Wave I of the adolescent health data, to see if the same relationships hold. I can also see if adolescent indicators of BMI affect adult outcomes in Wave III, to study the role of childhood socialization in adult outcomes. More research can be done on the types of ties, to see if directed ties have a greater influence than mutual ties between adolescents. There is also room to study other models with income and BMI. I did find in my modeling that a logarithmic function did not help explain the relationship, but perhaps other nonlinear models would provide me with a better framework from which to approach this question.

Figure 6 – School Average Income and BMI

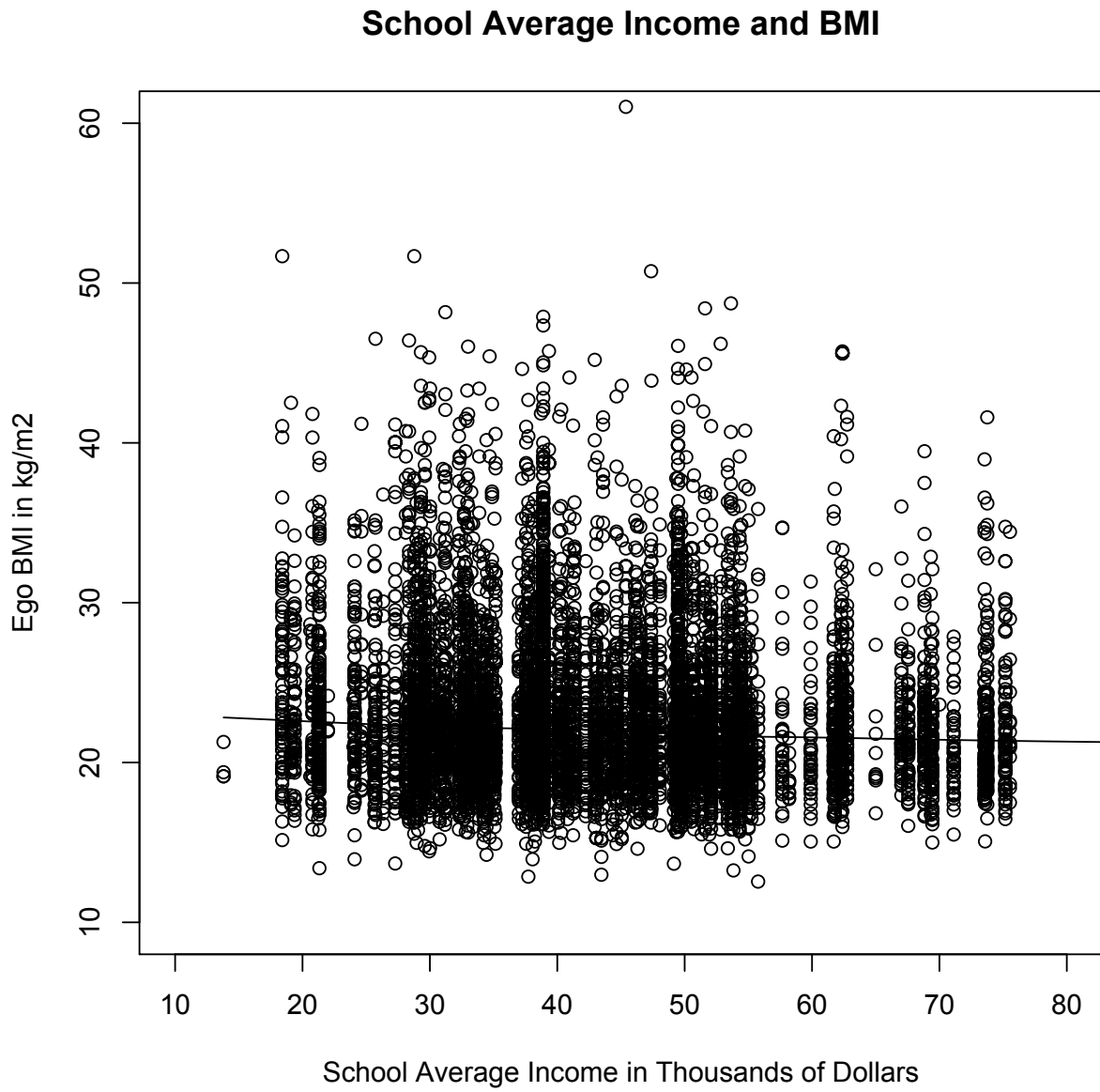


Figure 7 - Family Income and BMI

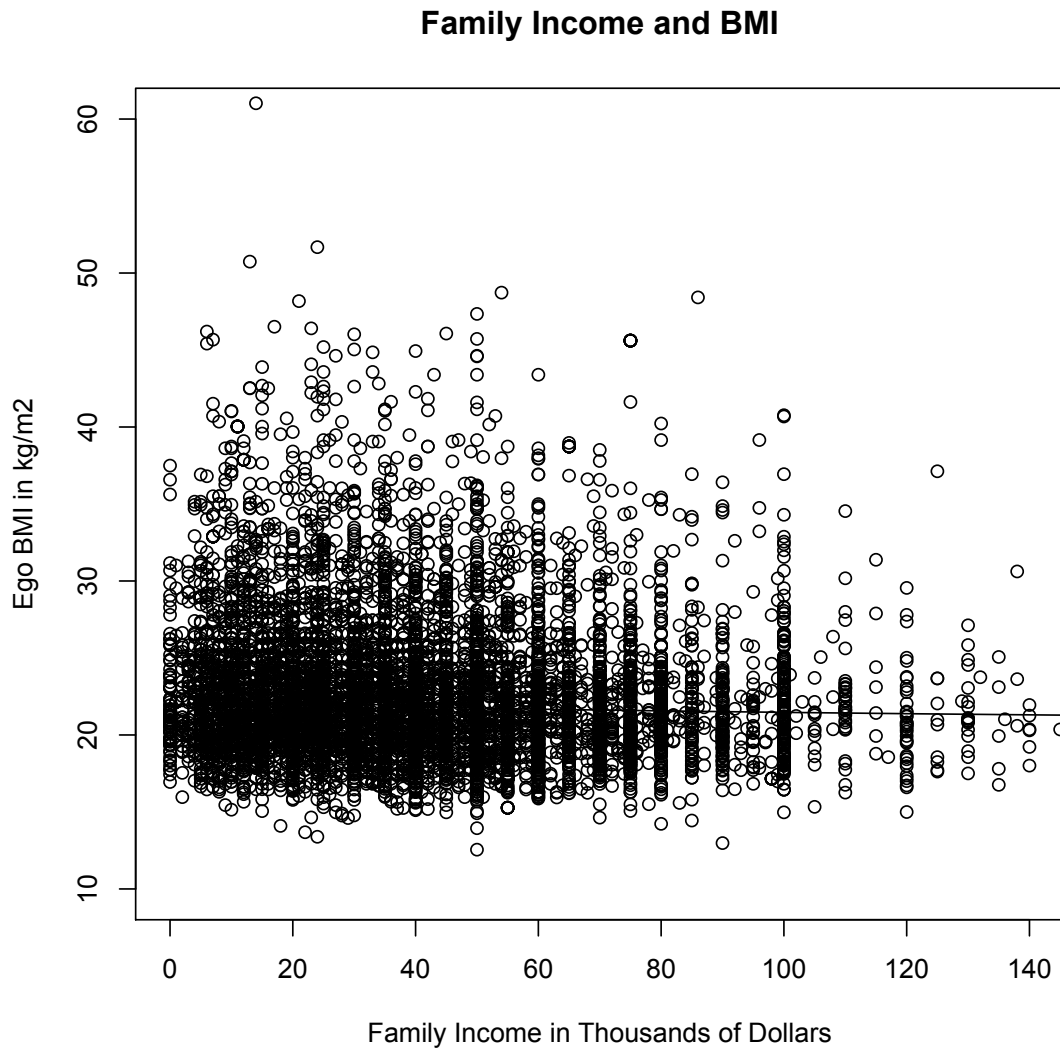


Figure 8 – Friends at 1 Degree Income and BMI

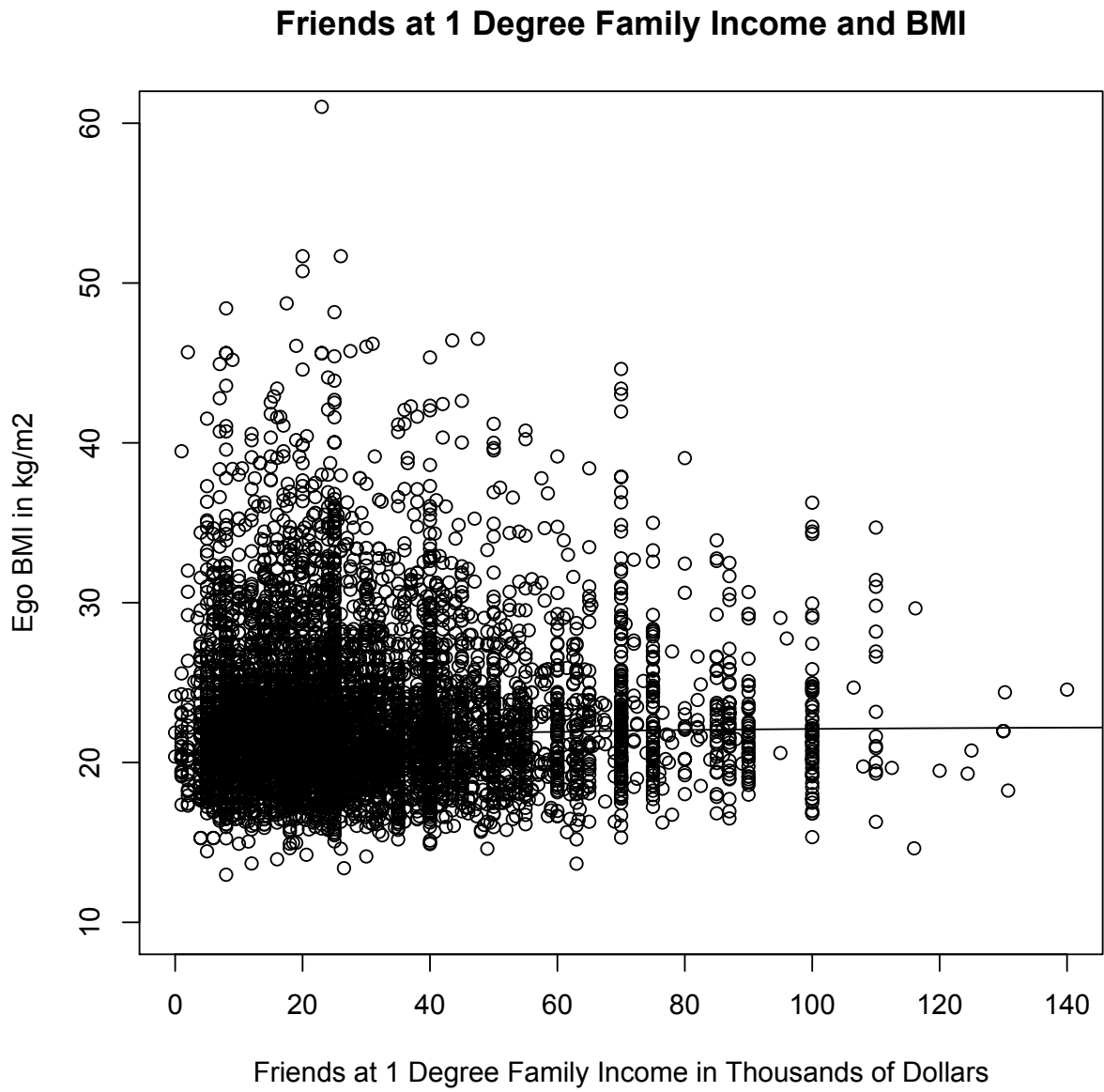


Figure 9 – Friends at 2 Degrees Income and BMI

Friends at 2 Degrees Family Income and BMI

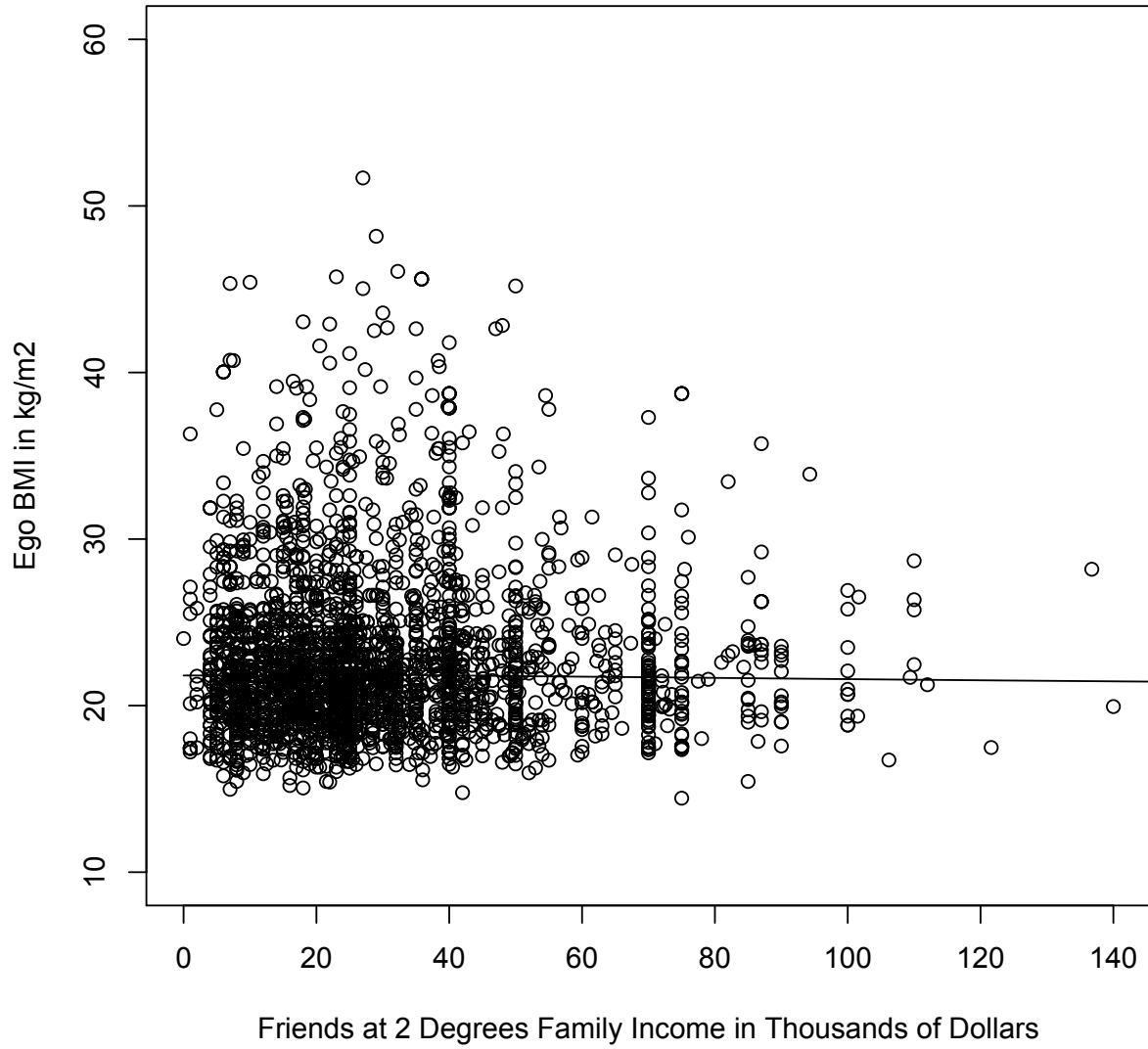
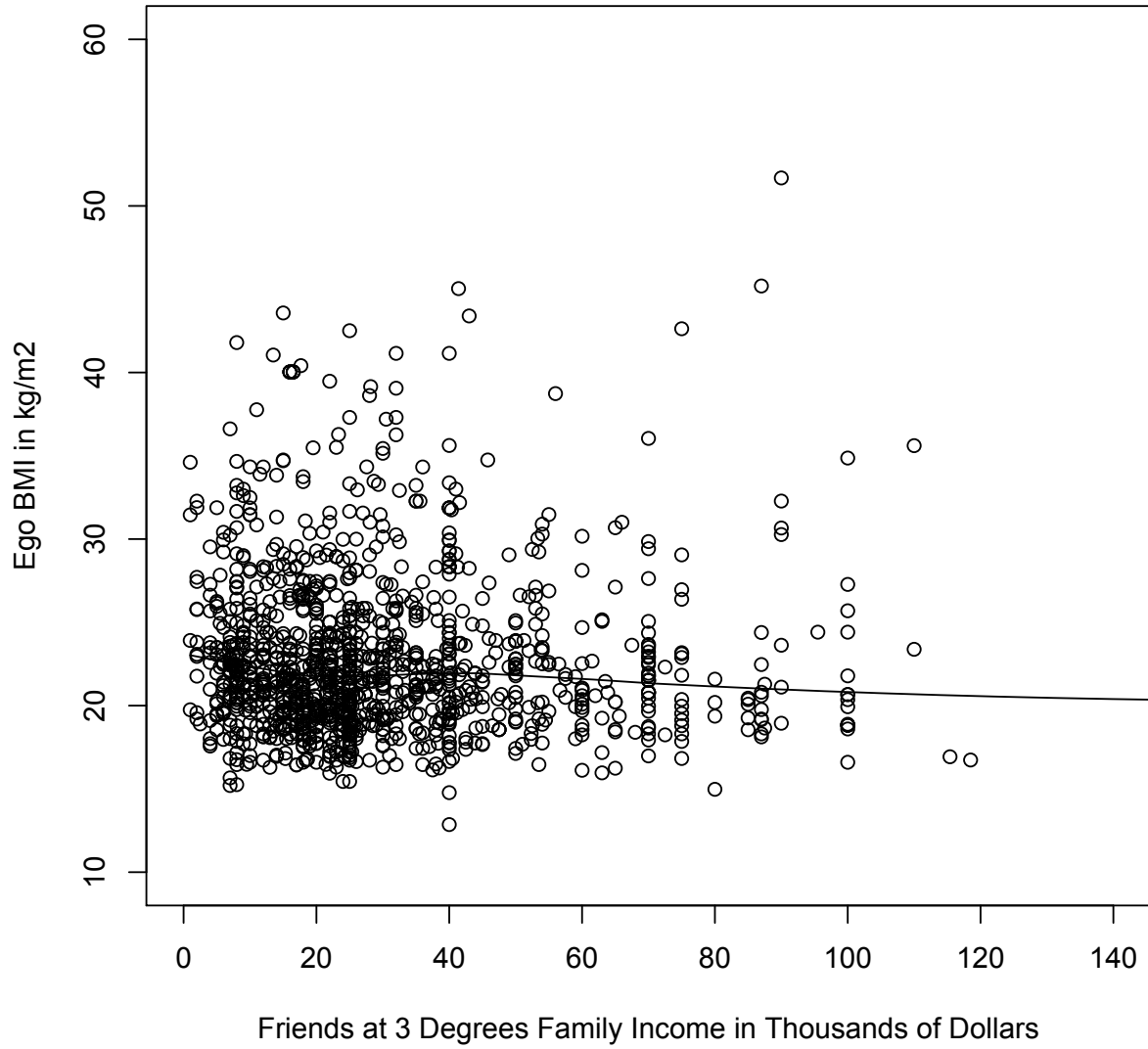


Figure 10 – Friends at 3 Degrees Income and BMI

Friends at 3 Degrees Family Income and BMI



CHAPTER 5: POLICY IMPLICATIONS

Restatement of Results

My results hold important implications with respect to the interplay of direct, contextual and network effects. It seems that in adolescent networks, contextual effects do play a statistically significant role in determining the BMI of adolescents. Adolescents going to richer schools will have lower BMIs, and an increase in average school income by 10,000 dollars is associated with a 1 kilogram per meter-squared decrease in BMI. Between ego income and school income, the contextual effect associated with school income was clearly stronger. This is important to recognize, as adolescents' health may be particularly affected by their school's physical environment and other socioeconomic factors associated with school average income. The role of direct effects was determined to be statistically insignificant after controlling for contextual effects.

I found that friends' income plays a small role in determining ego BMI, which was significant only at 2 degrees of separation from the ego. It seems that the strength of network effects is quite weak after controlling for direct effects and contextual effects, as a 10,000 dollar increase in friends' income at two degrees of separation is associated with a 0.3 kilograms per meter squared decrease in ego BMI. I will now begin a policy discussion regarding the value of contextual and network effects in public health interventions.

Contextual Effects as a Basis for Policy Changes

Implications of Results for Public Health Interventions

I will now discuss a few ideas based on recent interventions that have been attempted in schools. A health intervention is defined as an organized effort to modify behaviors of a sample

group in such a way that well-being is increased. I will end this discussion with a review of a recent study that emphasized the value of interventions as a way of lessening the negative impact of contextual effects. Given that my research found the school average income variable to be the most important determinant of BMI, I focus this section of the thesis on ways to improve health at the school level. I begin with a discussion of the Children WIC Reauthorization act of 2004, which provides context for many of the interventions that I discuss in this section.

The Child Nutrition and WIC Reauthorization Act

In 2004, this act was adopted by the U.S. Federal Government in response to the growing obesity trend among children. The act required all local education agencies participating in the National School Lunch program to create local wellness policies by mid-2006 (Hoxie-Setterstrom). These policies were supposed to entail the creation of task forces that would develop “goals for nutrition education, an assurance that school meal nutrition guidelines meet the minimum federal school meal standards, guidelines for foods and beverages sold or served outside of school meal programs, and goals for physical activity and other school-based activities” (McConnell). However implementation and evaluation components of this bill were not addressed in the mandate, so these components were left to the discretion of local school districts. This lack of explicit federal regulation became the source of many problems with the WIC Reauthorization Act.

Interventions Involving School Nurses: An Innovative Solution

A recent study found that the WIC Reauthorization Act was particularly unsuccessful – only one district in one large suburban county in Minnesota met all of the federal requirements

outlined in the bill (Hoxie-Setterstrom). This study advocated for an intervention program based on the knowledge of nurses, who have the most direct contact with children at schools. Indeed, “opportunities still exist to create comprehensive and stronger policies to effectively guide school environments” (Hoxie-Setterstrom). The study ultimately advocated for policy development with the input of school nurses, who can “educate stakeholders and district policy makers regarding the best practice for wellness policies, obesity prevention, and the connection to a productive learning environment” (Hoxie-Setterstrom). Indeed, nurses have the most information about students and their eating and exercise habits, given the close proximity of school nurses to the adolescents in question. My research would support such collaborative initiatives, given their potential for improving upon existing intervention models. Nurses have the most knowledge of factors related to direct and contextual effects, making them invaluable resources for interventions.

An Example of a Successful Intervention

A recent intervention was organized for 1349 students in grades four to six from 10 schools in a US city in the Mid-Atlantic. The study administered an intervention involving school self-assessment, nutrition education, nutrition policy, social marketing and parent outreach (Foster). Because this intervention is such a good representation of other public health interventions that have been attempted over the past decade, I will discuss it at length here. It is also representative of an intervention aimed at the contextual level. Given the results of my research, such an intervention would be ideal because it targets the most statistically significant of the determinants of BMI.

The self-assessment portion of the intervention involved the CDC School Health Index, which was followed by a Nutrition Advisory Group created at each school. From these self-assessments, schools developed action plans for change. The staff training portion involved approximately 10 hours per year of training in nutritional education. Along with the education came many promotional materials that could be used in the classroom. The nutrition education aspect of the intervention provided 50 hours of food and nutrition education per year to each student, so that students could understand the role of food choices in determining behavior. In nutrition policy, all of the food sold by intervention schools was changed to meet the standards set by the Dietary Guidelines for Americans. In social marketing, students who purchased healthy snacks and beverages were given raffle tickets, and raffle prizes included bicycles, indoor basketball hoops, and other prizes that would encourage activity. Family outreach programs were carried out by nutrition educators through “home and school association meetings, report card nights, parent education meetings, and weekly nutrition workshops” (Foster). Parents were encouraged to have their kids participate in the 2-1-5 challenge, which involved less than 2 hours of per day of television and video games, an hour or more of physical activity per day, and five or more fruits and vegetables per day.

This study ultimately found that in the control schools, 14.9% of children became overweight after 2 years, compared to just 7.5% in the intervention schools. “After controlling for gender, race/ethnicity, age and baseline prevalence, this study found that the predicted odds of overweight prevalence were 35% lower for the intervention group” (Foster). The intervention was found to be particularly important for black students. The unadjusted hours of total inactivity increased by approximately 3% in the control group, and decreased by approximately 9% in the intervention group. This study highlights how effective interventions aimed at the contextual

level can be. This makes sense given the results of my research, which suggested that the school average income contextual effect is the most significant of all variables. Interventions that attempt to mitigate the effects of a poor school would thus be expected to be quite effective.

Guidelines at the School Level

There are a number of steps that can be taken by schools to “create environments that are conducive to healthy eating and physical activity” (McConnell). For example, schools can start providing healthy foods in school-related events and practices, including parties, dinners and fundraisers. Schools can also modify schedules to support physical education activities, using physical activity as a way learn and maximizing the time given to physical activity in the daily schedule. In a more general sense, school must begin complying with guidelines set down by the Children WIC Reauthorization Act of 2004, which has policies designed to “promote student health and contribute to the reduction of childhood obesity” (McConnell).

Schools can also begin leading interventions at a broader level, given that friends have access to “parents and caregivers, school administrators, classroom teachers, physical education teachers, counselors, and community leaders” (McConnell). The incredible reach of schools makes them the ideal starting point for interventions. For example, through the school, parents can receive information on how to provide health food to their children.

The Effectiveness of Interventions

A recent study considered a systematic review of published studies of school-based interventions aimed at reducing Body Mass Index (BMI) of children (Lavelle). The authors of this study looked only at studies that reported a mean change in BMI or had enough data to

calculate the mean change in BMI from pre-intervention to post-intervention. Results indicated that for interventions that do not include a physical activity component, the evidence of a significant BMI reduction was lacking. The absolute reduction in BMI was found to be 0.17 kilograms per meter squared, which is statistically significant and “clinically insignificant at the individual level” (Lavelle). At the population level, however, such results could produce important health benefits for the community. This study shows the general value of public health interventions as an effective way to combat the contextual effects problem. It seems that public health interventions do indeed have an impact on BMI, perhaps making up for the challenges associated with having a poor school that lacks funding for physical activity.

However, there are studies that have found that physical activity does not have a significant impact upon the prevalence of obesity in schools. A slightly older study conducted in 2009 used randomized controlled trials and controlled clinical trials “that had objective data for BMI from before and after the intervention” (Harris). The authors of this study found that school-based physical activity interventions did not improve BMI. This study suggests a number of alternate explanations, including the possibility that there may have been a significant decrease in BMI for a small subset of children, “but the effect was attenuated in the assessment of the entire population” (Harris). This holds important implications for my research, which failed to find any statistically significant effect of friends’ income on BMI. It is possible that for some subset of the add health population, friends’ income has been quite important in determining BMI. This study also brings up the possibility that the observed association seen in many studies between interventions and reductions in BMI could be reverse, in that increased physical activity occurs as a downstream effect of lower weight. This is a valuable point and is worth considering seriously as further interventions are evaluated.

When considering funding at the state and local levels, my thesis ultimately supports initiatives that provide funding for school-based interventions. Given the impact that context has on BMI, it is essential that we take steps to improve this context.

Ideas for Statewide and Nationwide Campaigns and Policies

The most recent nationwide campaign is First Lady Michelle Obama's "Let's Move" campaign against childhood obesity. This campaign has the potential to be very effective because it complements many local obesity prevention initiatives. The campaign is coordinated at the federal level and makes efforts to create local, state and national partnerships to combat obesity. This is a unique effort and deserves to be supported.

My research findings advocate for interventions that involve massive partnerships of local, state and national organizations. While the 2004 mandate was a step in the right direction, it was far too weak of a policy measure to have any substantive impact. One idea is to "encourage competition among districts, by linking school board goals to wellness indicators" (McConnell). Another important nationwide policy would be one that provides kitchens in school buildings. It is through kitchens that schools can begin producing healthier foods, rather than providing commodity foods that are often unhealthy.

Improving lunchtime meals

Industry must also be regulated more closely, so that its products "reflect the upcoming Dietary Guidelines for Americans" (McConnell). Indeed, health initiatives in schools fail if the lunch lines continue to provide unhealthy food. If junk food is to be replaced with healthier food, then nationwide campaigns must provide funding to school feeding programs to account for the

higher cost of providing fresh fruits and vegetables. Renewed efforts need to be put behind program such as the 5-a-day program, which encourages healthy eating habits in all schools. There exists a set of US Department of Agriculture guidelines for school meals that does not yet conform to the 2005 US dietary guidelines. This is a national problem that must be fixed so that schools are given clear guidelines with respect to food requirements.

Network Effects

It is true that my research found a small role with respect to the role of friends' income on ego BMI. However, assuming that friends' income does have some small, statistically significant impact on ego BMI, we can think of creative ways to encourage people of different income backgrounds to come together. As a general principle, this research extends to the importance of reducing income inequality within society. If the poor are made less poor, then the negative effect of income on obesity is mitigated. A second consequence of this research is clear in urban development. Mixed income housing would be more likely to bring adolescents of various incomes together. If poor children associate with a broader range of adolescents of various incomes, then their socioeconomic risk factor for obesity may be mitigated. A third consequence of this research is the development of after-school programs that bring youth of various backgrounds together. Team events and social gatherings that transcend income boundaries should be encouraged, so that youth of different income backgrounds can benefit from each others' company. Interventions from a network perspective are fresh and innovative ways to reconsider old models of public health studies.

Interventions based on this research will involve novel solutions, where we must "address the personal connections of the people we are trying to help" (Christakis and Fowler). This is no

easy proposition, given that affecting networks is not as precise of a method as subsidizing healthy food or creating infrastructure to support healthy behavior. We can think of programs designed to bring people of various backgrounds together. “When we target the periphery of a network to help people reconnected, we help the whole fabric of society, not just any disadvantaged individuals at the fringe” (Christakis and Fowler).

Conclusion

Ultimately, my research supports more comprehensive models of the determinants of obesity. I found that friends’ income explained much less of the variation in BMI than did school average income. This suggests that models for interventions should be aimed at improving characteristics associated with schools and the context in which adolescents live. It seems that national initiatives that maintain partnerships with local and state-level organizations can successfully direct such interventions. The role of networks must be studied further, and may lead to unique intervention strategies.

REFERENCES

1. Ball K, Abbott G, Cleland V, Timperio A, Thornton L, Mishra G, Jeffery RW, Brug J, King A, Crawford D. Resilience to obesity among socioeconomically disadvantaged women: the READI study. *Int J Obes (Lond)*. 2011 Sep 20. doi: 10.1038/ijo.2011.183.
2. Bjornstrom EE. An examination of the relationship between neighborhood income inequality, social resources, and obesity in los angeles county. *Am J Health Promot*. 2011 Nov;26(2):109-15. PubMed PMID: 22040392.
3. Brown BB, Yamada I, Smith KR, Zick CD, Kowaleski-Jones L, Fan JX. Mixed land use and walkability: Variations in land use measures and relationships with BMI, overweight, and obesity. *Health Place*. 2009 Dec;15(4):1130-41. Epub 2009 Jul 4.
4. CDC. CDC's state-based nutrition and physical activity program to prevent obesity and other chronic diseases. Atlanta, GA: US Department of Health and Human Services, CDC; 2010.
5. CDC. Recommended community strategies and measurements to prevent obesity in the United States. *MMWR* 2009;58(No. RR-7).
6. Centola D. The spread of behavior in an online social network experiment. *Science*. 2010 Sep 3;329(5996):1194-7.
7. Chang VW, Lauderdale DS. Income disparities in body mass index and obesity in the United States, 1971-2002. *Arch Intern Med*. 2005 Oct 10;165(18):2122-8. PubMed PMID: 16217002.
8. Christakis NA, Fowler JH. Contagion in Prescribing Behavior Among Networks of Doctors. *Marketing Science*. 2010 May.
9. Christakis NA, Fowler JH. The spread of obesity in a large social network over 32 years. *N Engl J Med*. 2007 Jul 26;357(4):370-9.
10. Christakis, Nicholas and Fowler, James. Connected: The Surprising Power of Social Networks and how they Shape our Lives. New York: Back Bay Books, 2009. Print.
11. de la Haye K, Robins G, Mohr P, Wilson C. How physical activity shapes, and is shaped by, adolescent friendships. *Soc Sci Med*. 2011 Sep;73(5):719-28. Epub 2011 Jul 12. PubMed PMID: 21802807.
12. Easley, David and Kleinberg, Jon. Networks, Crowds and Markets. Cambridge: Cambridge University Press, 2010. Online.
13. Ewing R, Schmid T, Killingsworth R, Zlot A, Raudenbush S. Relationship between urban sprawl and physical activity, obesity, and morbidity. *Am J Health Promot*. 2003 Sep-Oct;18(1):47-57.
14. Foster GD, Sherman S, Borradaile KE, Grundy KM, Vander Veur SS, Nachmani J, Karpyn A, Kumanyika S, Shults J. A policy-based school intervention to prevent overweight and obesity. *Pediatrics*. 2008 Apr;121(4):e794-802.
15. Fowler JH, Christakis NA. Estimating Peer Effects on Health in Social Networks. *J of Health Economics*. 2008 Sep 27(5): 1400-1405.
16. Gordon-Larsen P, Nelson MC, Page P, Popkin BM. Inequality in the built environment underlies key health disparities in physical activity and obesity. *Pediatrics*. 2006 Feb;117(2):417-24.

17. Harris KC, Kuramoto LK, Schulzer M, Retallack JE. Effect of school-based physical activity interventions on body mass index in children: a meta-analysis. CMAJ. 2009 Mar 31;180(7):719-26. Review.
18. King, Gary; James Honaker, Anne Joseph, and Kenneth Scheve. "Analyzing Incomplete Political Science Data: An Alternative Algorithm for Multiple Imputation", American Political Science Review, Vol. 95, No. 1 (March, 2001): Pp. 49-69.
19. Lavelle HV, Mackay DF, Pell JP. Systematic review and meta-analysis of school-based interventions to reduce body mass index. J Public Health (Oxf). 2012 Jan 20. [Epub ahead of print] PubMed PMID: 22267291.
20. Leigh JP, Du J. Are low wages risk factors for hypertension? Eur J Public Health. 2012 Jan 18. [Epub ahead of print] PubMed PMID: 22262559.
21. McConnell P, Wendel J. Solving the Child Obesity Problem: How Schools Can Be Part of the Solution. ICAN. 2010 2:232. Review.
22. Nelson MC, Gordon-Larsen P, Song Y, Popkin BM. Built and social environments associations with adolescent overweight and activity. Am J Prev Med. 2006 Aug;31(2):109-17.
23. Newman, Mark. Networks: an Introduction. New York: Oxford University Press, 2010. Print.
24. R Development Core Team (2011). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL <http://www.R-project.org/>.
25. Udry JR (2003) The National Longitudinal Study of Adolescent Health (Add Health), Waves I & II, 1994–1996; Wave III, 2001–2002 [machine-readable data file and documentation]. Chapel Hill, NC: Carolina Population Center, University of North Carolina at Chapel Hill.
26. US Department of Health and Human Services, Centers for Disease Control and Prevention. Morbidity and Mortality Weekly Report. 14 January 2011.
27. Valente TW, Fujimoto K, Chou CP, Spruijt-Metz D. Adolescent affiliations and adiposity: a social network analysis of friendships and obesity. J Adolesc Health. 2009 Aug;45(2):202-4. Epub 2009 Mar 17.
28. Wang C, Hou XH, Zhang ML, Bao YQ, Zou YH, Zhong WH, Xiang KS, Jia WP. Comparison of body mass index with body fat percentage in the evaluation of obesity in Chinese. Biomed Environ Sci. 2010 Jun;23(3):173-9. PubMed PMID: 20708495.
29. Wang Y, Chen X. How Much of Racial/Ethnic Disparities in Dietary Intakes, Exercise, and Weight Status Can Be Explained by Nutrition- and Health-Related Psychosocial Factors and Socioeconomic Status among US Adults? J Am Diet Assoc. 2011 Dec;111(12):1904-11. PubMed PMID: 22117667.
30. Wasserman, Stanley and Faust, Katherine. Social Network Analysis: methods and applications. New York: Cambridge University Press, 1994. Print.
31. Wasserman, Stanley and Galaskiewicz, Joseph. Advances in Social Network Analysis. Thousand Oaks: SAGE Publications, 1994. Print.
32. Xie B, Chou CP, Spruijt-Metz D, Liu C, Xia J, Gong J, Li Y, Johnson CA. Effects of perceived peer isolation and social support availability on the relationship between body mass index and depressive symptoms. Int J Obes (Lond). 2005 Sep;29(9):1137-43.