Public Policy Institute *of* California

Obesity Among California Adults: Racial and Ethnic Differences

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2006

Library of Congress Cataloging-in-Publication Data

Lee, Helen, 1975-

Obesity among California adults : racial and ethnic differences / Helen Lee

p. ; cm.

"August 8, 2006"

Includes bibliographical references.

ISBN-13: 978-1-58213-122-1

ISBN-10: 1-58213-122-8

1. Obesity—Social aspects—California. 2. Obesity—California—Cross-cultural studies. I. Public Policy Institute of California. II. Title.

[DNLM: 1. Obesity—epidemiology—California. 2. Obesity—ethnology—California. 3. Adult—California. 4. Health Policy—California. 5. Obesity—prevention & control—California. 6. Risk Factors—California. WD 210 L478o-2006]

RA645.O23L44 2006

362.196'398009794—dc22

2006029618

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Foreword

National attention has recently begun to focus on the alarming incidence of obesity among Americans. Obesity has been portrayed as a public health challenge of immense proportions—with implications for the productivity of the labor force and dramatic increases in health care costs today and for years to come. PPIC research fellow Helen Lee has looked at this national phenomenon to see whether it has also affected Californians. She found that in spite of the state's reputation as a state of sunshine and health-conscious individuals, the trends toward obesity in California mirror the national trends. The average man and woman gained between 12 and 15 pounds between 1990 and 2003. Disparities between racial and ethnic groups were also striking. For example, black and Hispanic women were between 14 and 19 pounds heavier than white women, depending on their height. Not surprisingly, the risk of obesity is also related to socioeconomic status. Those who have lower income and education levels, and those living in poor neighborhoods, have a higher risk of obesity.

Perhaps the most important conclusion of this study is that even after controlling for individual and neighborhood characteristics, much of the higher risk of obesity among black and Hispanic women relative to white women remains unexplained. In the end, individual characteristics matter the most when predicting the risk of obesity. This is both good news and a challenge for policy interventions. It *is* possible to change personal behavior, as has been the case with successful national programs to discourage smoking. On the other hand, targeting programs to people and neighborhoods where the risk is highest presents a challenge simply because of limited funding and the tension between a national and local agenda. We trust that the findings in this report will help the state of California deal with its own public health challenge—today and for years to come.

David W. Lyon
President and CEO
Public Policy Institute of California

Summary

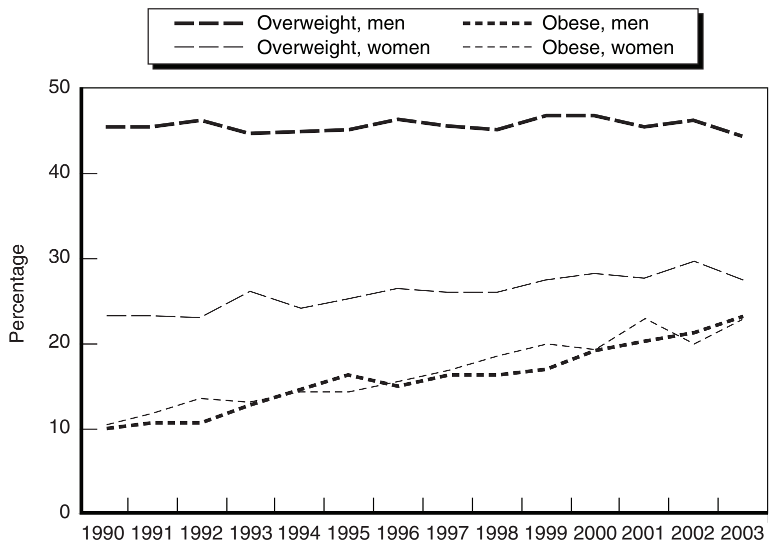
Health researchers have estimated that obesity and obesity related behaviors, including poor dietary practices and physical inactivity, account for approximately 300,000 preventable deaths annually in the nation (McGinnis and Foege, 1993). High body mass index (BMI) has been linked to a number of serious health risks, ranging from cardiovascular disease to diabetes. Many of the health conditions associated with obesity are largely irreversible and, once developed, must be managed for life. However, obesity itself is arguably reversible, suggesting an important role for health policy, particularly in regard to health promotion, prevention, and awareness campaigns that aim to encourage behavioral changes in physical activity and dietary intake.

Research at the national level has documented a trend of a steady and marked rise in obesity prevalence, particularly over the last 20 years. Obesity rates among Californians follow a similar pattern. However, considering only overall trends masks important variation among population subgroups, most notably along racial, ethnic, and socioeconomic lines. The report brings insight into the role of numerous individual and neighborhood characteristics in predicting BMI. In particular, we focus on the notable disparities in the patterning of high BMI among whites, blacks, Hispanics, and Asians. These differences pose particular policy challenges in California given the size and diversity of its population. Understanding these disparities and the determinants of BMI is important for designing and choosing among various public health strategies that seek to target resources broadly and toward those most at risk.

Key Facts and Findings

Trends in Obesity Prevalence, 1990 to 2003

As shown in Figure S.1, since 1990, adult obesity rates have more than doubled for the state, for both men and women.[1] In 1990, around 10 percent of Californian men and women could be considered medically obese. By 2003, the age-adjusted obesity prevalence rate for men and women was over 20 percent, such that almost 4.5 million



SOURCE: Author's calculation using the 1990–2003 CDC Behavioral Risk Factor Surveillance System.

NOTES: Estimates are shown for adults, ages 20–69, and are weighted. Prevalence rates are age-standardized to the 2000 Census population distributions.

Figure S.1—Trends in Obesity and Overweight Distributions in California, 1990–2003, by Sex

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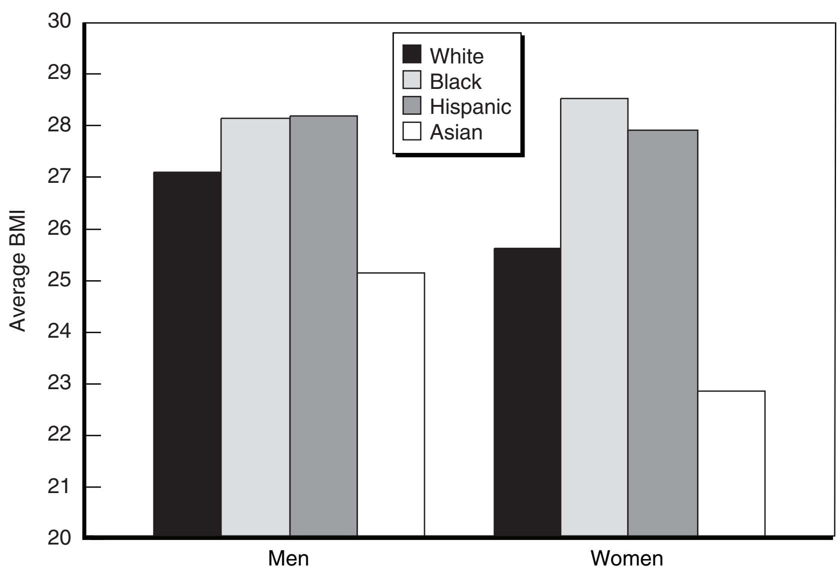
[1]Obesity and overweight are graded classifications of weight based on one's BMI. Body mass index is a measurement that adjusts weight for height (BMI = weight in kilograms/height in meters squared) (World Health Organization, 2004). Individuals with a BMI of 30 or higher are considered medically obese. Individuals with a BMI between 25 and 29.9 are considered overweight.

California adults (ages 20–69) were obese. The trends and levels in obesity and overweight prevalence seen in Figure S.1 are comparable to those of the rest of the country. Moreover, there is no evidence to suggest that this trend will reverse in the near future, suggesting that obesity prevention and modification are particularly topical issues for both the state and the nation.

Racial and Ethnic Differences in Average Body Mass Index

We find, as others have, that differences in average BMI between Hispanics and whites and blacks and whites are sizable, particularly for women in California (Figure S.2). The difference in average BMI between black and Hispanic women relative to white women is about



SOURCE: Author's calculation using the 2003 California Health Interview Survey.
NOTES: The figure shows the predicted average BMI for the major racial/ethnic groups, after controlling for age and age squared. Estimates are weighted.

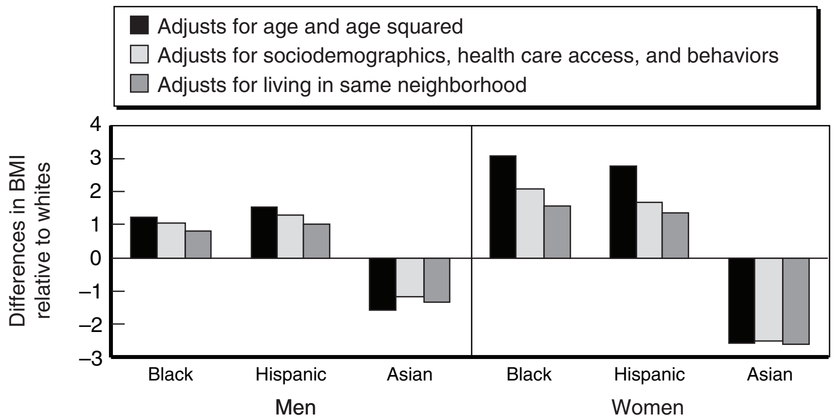
Figure S.2—Average BMI Among California Adults, 2003, by Race/Ethnicity and Sex

three points, which translates to a notable 18 pound gap for a woman of average height—5'4". That is, although the average 5'4" tall white woman in California in 2003 weighed about 149 pounds, the average Hispanic woman of similar height weighed about 163 pounds and the average black woman of similar height weighed 166 pounds. Racial/ethnic disparities in BMI also exist for men, but the differences are not nearly as stark as they are for women. We also find that Asian men and women have relatively advantageous BMI profiles, with average weight-for-height measures that largely fall within the normal classification range.

What Accounts for Racial/Ethnic Differences?

Blacks and Hispanics in California tend to have higher poverty rates and lower levels of educational attainment than whites. Prior research has demonstrated that obesity risk follows a socioeconomic gradient, such that those who have higher income and more education have lower BMI. Thus, racial and ethnic differences in BMI may reflect the differing socioeconomic status of blacks and Hispanics compared to whites. Indeed, Figure S.3 shows that part of the black-white and Hispanic-white disparity in BMI is driven by differing socioeconomic status and other characteristics among these groups. However, a substantial part of the disparities cannot be accounted for by personal characteristics. In addition, we cannot explain why Asians have lower BMI than whites by adjusting for any of the characteristics we consider.

We further find that when we look at differences in BMI among residents who live in the same neighborhood (defined through zip code tabulation areas), as shown in the last bar of Figure S.3 for each racial/ethnic group, the disparities noted above attenuate slightly. This finding suggests that neighborhood environment plays a role in predicting BMI and explaining racial/ethnic disparities. Even so, it is beyond the scope of our data and analyses to establish causal relationships between neighborhood characteristics and high BMI. Nonetheless, our findings suggest that obesity prevention efforts that focus solely on individual behavioral modification may have a limited impact without also addressing how neighborhood environments make such behavioral changes more or less attainable.



SOURCE: Author's calculation using the 2003 CHIS.

NOTES: The figure shows racial/ethnic differences in BMI relative to whites, adjusted for various factors. Estimates are weighted. The first bar shows racial/ethnic differences that have been adjusted only for age and age squared (and not neighborhoods) for comparative purposes. The second bar adjusts for age (and age squared) and other personal characteristics (such as nativity, education, income, health care access/use, and behavior). The last bar adjusts for all personal characteristics and also for living in the same neighborhood (see Appendix B for a discussion of methods). All estimates are statistically significantly different from those for whites at the 5 percent level.

Figure S.3—Differences in BMI, Adjusted for Personal Characteristics and Living in the Same Neighborhood, 2003, by Race/Ethnicity and Sex

The Role of Neighborhood Context

We investigate the role of neighborhood characteristics on BMI in more detail, as prior research has demonstrated that aspects of neighborhood environment (including concentration of food establishments, neighborhood poverty, and community infrastructure) may play a role in encouraging healthier lifestyles or, conversely, hindering healthier behaviors. We find that neighborhood disadvantage (measured by poverty rate) is associated with slightly higher BMI among women, above and beyond individual socioeconomic status. For both men and women, we also find that living in a neighborhood with a higher concentration of white residents—independent of one's individual race/ethnicity—is associated with lower BMI. However, individual characteristics matter much more than neighborhood characteristics in explaining obesity risk. Furthermore, even after we consider the joint roles of personal and neighborhood characteristics, a sizable portion of the higher risk of obesity among black and Hispanic women relative to white women remains unexplained.

Findings from Obesity Prevention and Evaluation Studies

Although this report does not assess the efficacy of any specific obesity prevention program, we bring insight to policymakers and health officials on strategies for obesity prevention by reviewing current and previous policy and public health responses. Overall, we find that many of the programs, whether in the form of public health education campaigns or community and work-placed interventions, that aim to improve diet and exercise and reduce obesity risk do not detect a measurable or sustained effect on behavior or BMI. We believe that this limited success may be partly because of the need for longer-term interventions and longer-term evaluations and partly because of the need for more carefully designed research studies and interventions. At the same time, there is evidence that community-based, work-based, and larger public health campaigns increase awareness of risk factors and the benefits of engaging in health-promoting behaviors. Yet making sure that the public education effort and message has relevancy and promotes a practicable behavioral change for diverse populations remains a timely issue that health officials should take into account.

Conclusions

Our results suggest that obesity risk is multifaceted and perhaps multilevel, with no clear or simple explanatory answers. The ultimate efficacy of public health-related interventions is conditional on understanding how "risk" operates. Some population subgroups in California, namely blacks and Hispanics, are at significantly greater risk for obesity in ways that this report cannot fully account for. In 2003, almost 4.5 million Californians (ages 20–69) could be considered medically obese, about 40 percent of whom are of Hispanic origin. Because Hispanics constitute the fastest-growing population subgroup in the state, addressing the high obesity rates and potential risk for obesity among this group represents an important public health challenge.

Other results that we point to in the report reveal that the known correlates of obesity, including education, poverty, smoking, and walking, are significantly associated with BMI among whites in ways that we expect based on findings from prior research studies. Yet many of these same factors are not as important for understanding BMI among blacks, Hispanics, or Asians. These results provide further evidence that the processes and mechanisms associated with obesity are nuanced. Furthermore, many intervention studies have found no measurable effect on behavioral change or weight status, perhaps because the approach taken was too broad or relatively short term in scope. Taken together, these findings underscore the importance of considering a tailored and long-term approach to addressing obesity prevention.

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Acknowledgments

This work has benefited from the perceptive comments, suggestions, and assistance provided by a number of people. In particular, I am grateful to Marianne Bitler, Susan Foerster, Deborah Reed, and Catherine Ross for their careful and thoughtful reviews on earlier drafts. I would like to express my sincere thanks to Rebecca Steinbach, whose capable research assistance contributed to this project from beginning to end. I am also thankful to Brandon Traudt and the staff at UCLA's Center for Health Policy Research for their provision of timely aid with remote data programming. Joyce Peterson's structural guidance and Lynette Ubois's editorial assistance are acknowledged with appreciation. I also thank the members of PPIC's advisory council for their insights. Notwithstanding these contributions, the opinions, interpretations, and any errors of fact expressed in this report are mine alone and do not necessarily reflect the views of the Public Policy Institute of California.

1. Introduction

Today, about one in five adults in California is considered medically obese, a statistic that parallels that of the nation.[1] In contrast, in the mid-1980s, that number was around one in ten, suggesting that lay and media reports asserting an escalating obesity problem are not without some foundation.[2] Indeed, obesity prevalence has risen markedly for both the state and the nation, particularly in the past 20 years, with little indication that this trend will reverse in the near future (Thorpe and Ferraro, 2004).

Although sometimes framed as an individual or cosmetic problem, obesity constitutes a serious public health issue. The health concerns regarding excess weight are considerable. High BMI is associated with numerous health risks, including hypertension, osteoarthritis, coronary heart disease, colon and breast cancer, and, most notably, Type 2 diabetes (Allison et al., 1999; Roth et al., 2004). Research has shown that adults who are obese and remain obese throughout middle and late

[1]Obesity is a classification based on one's BMI, in which individuals with a body mass index of 30 or higher are considered obese. Body mass index is a calculation that adjusts weight for height (weight in kilograms/height in meters squared). Most researchers consider this index a useful, although somewhat crude, approximation of body fat composition (World Health Organization, 2004). Other measures of adiposity (body fat), such as waist circumference and waist-to-hip ratio, are thought to be useful indicators of abdominal fat accumulation, which is positively related to BMI and such obesity-related illnesses as cardiovascular disease (World Health Organization, 2004). Waist circumference and waist-to-hip ratio vary at any given BMI level, suggesting that these measures, in addition to BMI, are valuable for identifying at-risk individuals. However, accurate information on waist or hip measurement is difficult to collect and is often lacking in national surveys. Therefore, most studies use BMI classifications.

[2]Estimates of obesity prevalence tend to vary depending on the survey data being examined. For example, Flegal et al. (1998), using the National Health and Nutrition and Examination Survey, estimated an obesity prevalence rate as high as 14 percent in the late 1970s and early 1980s. However, all national health surveys have documented similar trends in rising obesity rates since the late 1970s and early 1980s.

adulthood are at increased risk of disability and premature mortality (Himes, 2000; Ferraro and Kelley-Moore, 2003).[3] Furthermore, obesity may affect not just length of life but also its quality, including the ability to engage in some "normal" activities of daily living (e.g., dressing, bathing, running errands, and walking up stairs without physical difficulty). For these reasons and others, some scholars have argued that obesity exceeds the risks that other public health issues, such as smoking or problem drinking, incur on individual and population well-being (Sturm, 2002).

It is difficult to pinpoint the exact costs and consequences that obesity poses for the nation and the state, mainly because the task of isolating overweight and obesity as the underlying causes of various morbidities, disability, and lost worker productivity is challenging and somewhat discretionary. Researchers have attempted to calculate such approximations, however; a recent study estimated that 17 percent of excess deaths or preventable mortality was related to obesity (Mokdad et al., 2004). In 2001, the Surgeon General's report on obesity estimated that excessive weight costs the nation roughly $117 billion in direct (through prevention and treatment services) and indirect costs (e.g., work loss resulting from disability and death) (U.S. Department of Health and Human Services, 2001). It has been suggested that in 2000, physical inactivity, overweight, and obesity cost California $21.68 billion dollars in medical care expenses, workers' compensation claims, and lost productivity (Chenoweth, 2005). These figures indicate that obesity incurs sizable direct and indirect costs to society but, again, the precision of these estimates is best viewed cautiously, as "ballpark" approximations (Allison, Zannolli, and Venkat Narayan, 1999).

Disparities in Obesity

Part of the concern regarding obesity is that it is not an isolated health condition. Average BMI has increased for most racial and ethnic

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[3]Although there is some debate in the medical literature regarding how much excess body weight contributes to certain diseases and premature mortality, most researchers agree that conditions related to metabolic regulation, such as Type 2 diabetes, are undoubtedly linked to high BMI (see Roth et al., 2004, for a review).

groups, for both men and women, for almost all age groups, and across socioeconomic strata. At the same time, obesity tends to be unequally concentrated among certain racial and ethnic minority groups and mirrors larger socioeconomic inequalities. For example, non-Hispanic blacks are twice as likely as non-Hispanic whites to be obese according to national figures. Studies have also found significantly higher overweight and obesity rates among Hispanic-origin individuals than among whites (Flegal et al., 2002; Mokdad et al., 2003; Ross and Mirowsky, 1983). In addition, individuals with low education levels and limited incomes are more likely than those with higher education and incomes to be obese.

These disparities pose particular policy challenges in California given the racial, social, and economic diversity of its population. If these patterns hold true for California, obesity can arguably be seen as both an existing and an emerging health and social problem in the state. Thus, understanding disparities in and determinants of high BMI is an important and timely issue for designing and deciding among various public health approaches that seek to target resources broadly or toward those most at risk (Newsom et al., forthcoming).

Why Focus on Adults?

Although most public health officials have long recognized the need, policy consideration for obesity prevention and modification has been fairly recent and focuses primarily on children. For example, recent legislation has imposed bans on selling soda in public schools (SB 965 and SB 677) in an attempt to change school environments to encourage healthier dietary practices among children. Other states have already enacted mandatory physical education classes as part of the middle school and high school curriculum, in an effort to increase cardiovascular health among adolescents.

Although childhood obesity is a pressing problem, adult obesity is an equally concerning issue. The burden of adult obesity is not just borne by the individual; it ultimately exacts tolls on the family, health care system, taxpayers, and the workplace. Many of the co-morbid conditions associated with obesity are largely irreversible and typically develop in middle to late adulthood. Once these conditions have developed, an individual (and often, the individual’s partner or spouse, children, and other relations) must manage them for life. Furthermore, to the extent that children may model or shape their behaviors after their parents, and also because parents are key decisionmakers regarding food quality, food quantity, and extracurricular activities, understanding adult obesity is critical.

Adult obesity is arguably reversible, suggesting a potentially important role for health policy, particularly in regard to health promotion, obesity prevention, and awareness. At the same time, obesity is a complex problem, creating a quandary for policymakers who have often been faced with the task of allocating money to public health campaigns with little indication that such campaigns have proven effective in bringing about measurable weight control. Yet, as with other public health concerns, understanding the problem, increasing public knowledge, and addressing barriers to behavioral change are often the first steps in making progress toward the ultimate end of improving population health.

Research Objectives

This report focuses on adult obesity and documents its related risk factors in California. Specifically, we address the following questions:

- How has average body mass and obesity prevalence changed over the last 13 years in California?[4] How do these trends compare to those in the rest of the United States?
- Who is most at risk for obesity in California? What personal characteristics are most important for understanding high body mass?
- What role does the neighborhood environment play in understanding obesity risk?
- What evidence exists regarding obesity prevention initiatives and programs?

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[4]We examine trends in average BMI and obesity/overweight prevalence only from the early 1990s to 2003 because of data constraints. See Chapter 2 and Appendix A for more detail.

Overview

Chapter 2 traces trends over time in average BMI and obesity for California and the rest of the nation. Chapter 3 describes who is most at risk for high BMI, with specific emphasis on examining large racial/ethnic disparities. We also look at how risk factors for obesity vary for different racial/ethnic groups and find that some individual characteristics that explain high BMI among whites are not as important for understanding BMI among Hispanics, blacks, or Asians. Chapter 4 examines what role, if any, neighborhood characteristics (measured at the zip code tabulation area level) play in predicting obesity independent of individual characteristics. We pay particular attention to whether differing neighborhood environments can explain persistent racial/ethnic differences in obesity. Chapter 5 then gives an overview of research studies that review obesity prevention programs, broadly defined, and describes various policy and prevention options that are currently being debated in the literature. Finally, we conclude by outlining some key insights documented in this report and other research that may aid efforts toward obesity prevention.

A Note on Data and Definitions

We draw primarily from two main sources of data to study adult obesity: the 1990–2003 Behavioral Risk Factor Surveillance System (BRFSS) and the 2003 California Health Interview Survey (CHIS). The BRFSS has been collecting information on BMI and health behavior across states over the past 20 years. This makes it ideal for understanding state-specific time trends in addition to national-level trends (Chou, Grossman, and Saffer, 2004), which is our main goal in Chapter 2. In Chapters 3 and 4, we rely on the CHIS because it has better racial/ethnic diversity and much larger sample sizes, which enable us to analyze obesity risk in more statistical detail. In addition, as we will discuss in Chapter 4, to examine the role of neighborhood characteristics, we needed to construct a unique dataset that merged individual characteristics with neighborhood characteristics. Because the CHIS respondents were linked to neighborhood identifiers, it is an ideal dataset for examining the role of both personal and neighborhood factors. For more detail on the BRFSS and CHIS, readers are encouraged to read Appendix A. For more information on how we merged neighborhood information and measured neighborhood characteristics, please see Appendix B.

As have the vast majority of studies of obesity and BMI, we note here that we calculate BMI using self-reports of weight and height, which were collected in both these surveys. However, the accuracy of these self-reports can be questionable, especially as higher weight becomes more stigmatized in society. Studies that have compared objective measures (e.g., reports from medical charts or exams) to self-reports have found that individuals are largely forthright in their responses (e.g., Stewart, 1982), although there may be a tendency for underreporting weight.[5] Thus, if underreporting is present in the data analyzed throughout the report, our findings will be underestimates of true obesity prevalence and average BMI in California.

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[5]Underreports of weight may partly explain discrepancies between prevalence rates from the BRFSS (examined in Chapter 2) and those from the National Health and Nutrition Examination Survey (NHANES), a national health survey where respondents are weighed and measured by examiners (Flegal et al., 2002). Estimates based on the NHANES are typically higher than those estimated from BRFSS and other self-reported data.

2. Trends in Obesity Prevalence and Related Risk Factors

In recent years, the sheer abundance of mainstream media attention to the obesity "epidemic" in America raises the question of how much concern is based on rhetoric and how much on reality. In particular, California presents an unusual case in the popular consciousness—how can obesity be a public health concern in a seemingly health-conscious state (Hubler, 2000)? This chapter provides an overview of trends in obesity rates and average BMI in California and the rest of the United States, from 1990 to 2003. Our purpose is to illustrate what has happened to weight patterns over time in the state and to demonstrate that California has similar patterns to those in the rest of the nation. Using the Centers for Disease Control and Prevention (CDC)'s Behavioral Risk Factor Surveillance System data, we find patterns that indicate a steady escalation in obesity rates over the years, as has been consistently documented in national-level studies.[1]

What factors account for these trends? Ultimately, body weight is a function of how much energy one takes in (calories consumed) and how much energy one expends (through everyday activity and basal metabolism). Many researchers believe, although it is very difficult to prove in a cause-and-effect manner, that the obesity trends documented here and elsewhere are mainly due to imbalances on both sides of the energy equation (i.e., too much food and too little movement or exercise) (Taubes, 1998; Flegal et al., 2002). Unfortunately, we do not have information on caloric intake or expenditures in the BRFSS. However,

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[1]The BRFSS has been collecting information on health behaviors across states since 1984. However, because not all states participated in the early years (especially 1984–1988) and because California sample sizes are very small for certain sociodemographic subgroups in these years, we have chosen to examine survey years from 1990 and beyond (see Appendix A for more information on the BRFSS).

in Appendix C we show how reports of physical inactivity and dietary practices, using a basic indicator of fruit and vegetable consumption, have changed since the early 1990s.

We cannot identify the possible causes for the escalating trends from what is described in this chapter. Indeed, doing so is the topic of a much larger and controversial debate among health researchers and leading obesity experts, with no clear consensus. Therefore, we conclude the chapter with a brief discussion of the evidence based on national research that has attempted to explain rising obesity rates.

The Importance of Sex and Age When Examining BMI

Age is strongly associated with BMI, which tends to increase over the life course and decrease at the oldest ages. Because different groups have different age structures (e.g., women have a slightly older age distribution than men and Hispanics as a group are younger than whites) and because age distributions change slightly over time, it is important to account for these differences. We do so by age-standardization, in which we age-adjust BRFSS estimates to the 2000 Census population age distributions.[2] Using the 2000 Census as our base population allows us to easily compare estimates across different survey years.

Sex is also correlated with BMI; women tend to have lower average BMI than men. Thus, most of our figures in this chapter (and throughout the report) show separate estimates for men and women. Ideally, we would have liked to present estimates separately by racial/ethnic background as well. However, even in the later years of the BRFSS, state-specific sample sizes for certain nonwhite, sex-age groups became very small and statistically unreliable (particularly for blacks and Asians). Therefore, we show only figures based on estimates that are age-standardized and stratified by sex.

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[2]Age-standardization is essentially a weighting technique in which age group estimates obtained from the BRFSS for each survey year are reweighted to the 2000 population age distribution, using three age groups (20–39, 40–59, and 60–69). California estimates are age-standardized to the 2000 Census population age distributions for California. The estimates for the rest of the states are age-standardized to the 2000 Census population age distributions for the entire United States.

Trends in Average BMI

Figure 2.1 illustrates how weight in relation to height has changed from 1990 to the early 2000s. Californians' average BMIs are fairly similar to those of the population in the rest of the nation but often a little lower (by a difference of about 0.2 BMI points or about 1.0 to 1.5 pounds) depending on the survey year.[3] There are large sex differences in average BMI; women across the state and in the rest of the country have an average BMI that is around one point below that of men. One

SOURCE: Author's calculation using the 1990–2003 BRFSS.

NOTES: Estimates are shown for adults, ages 20–69, and are weighted. Estimates are age-standardized to the 2000 Census population.

Figure 2.1—Average BMI in California and the Rest of the United States, 1990–2003, by Sex

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[3]In some survey years, comparing California to the rest of the United States, the slightly lower average BMI for women is statistically significant at the 5 percent level (1990, 1994, 1995, and 1996). The average BMI for California men is also significantly lower than that for men in the rest of the country at the 5 percent level in certain years (1992, 1993, 1994, 1998, and 1999).

of the most notable (and well-documented) patterns that emerges is that average BMI has clearly risen over time in both California and the rest of the United States. In 1990, the average 5'4" tall woman in California weighed about 139 pounds, with an average BMI of about 24. In 2003, the average 5'4" California woman weighed 154 pounds, representing a 15 pound weight difference over the past 13 years. BMI for men in California also increased; the average 5'10" tall man in 2003 weighed about 12 pounds more than the average man of the same height in 1990.

Trends in Obesity and Overweight Prevalence

Average BMI provides an informative picture of where the average individual falls on the weight/height scale, but another common way to look at trends associated with weight is to examine the percentages distributed across weight classes or categories that are based on BMI.[4] As noted above, obesity is one such class (BMI ≥ 30). Other classes include overweight (BMI 25–29.9), normal weight (BMI ≥ 18.5 and < 25), and underweight (BMI < 18.5). According to these thresholds, a 5'4" tall woman would be considered obese if she weighed 174 pounds or more, overweight if she weighed between 145 and 173 pounds, and normal weight if she weighed between 107 and 144 pounds. Similarly, a 5'10" tall man would be obese at 209 pounds or higher, overweight at 174 to 208 pounds, and normal at 137 to 173 pounds.

National research demonstrates that although age-adjusted obesity rates were relatively stable through the 1960s and 1970s, a significant increase was documented by the early 1980s (Flegal et al., 1998). What we see in Figure 2.2 is that throughout the 1990s and early 2000s, age-adjusted obesity prevalence rates continued to increase for both men and women. Figure 2.2 also illustrates that the pattern of obesity rates in California is very similar to that of the rest of the country.[5]

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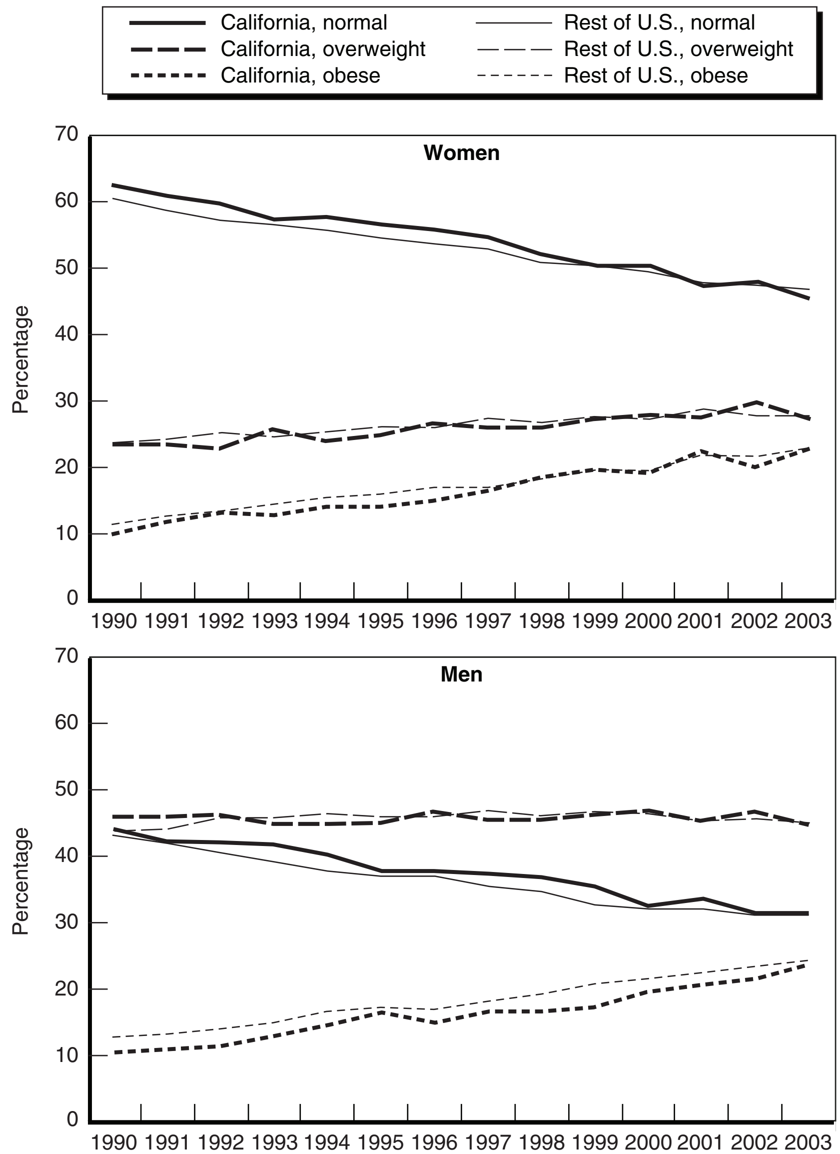
[4]These weight classes or thresholds are primarily based on differential health risks documented with varying BMI levels. Other studies in the literature use differing thresholds, but the BMI classifications used here are the most common and widely accepted (World Health Organization, 2004).

[5]For almost all survey years seen in Figure 2.2, no statistically significant differences (at the 5% level) in obesity, overweight, and normal weight prevalence were detected comparing California and the rest of the United States.



SOURCE: Author's calculation using the 1990–2003 BRFSS.

NOTES: Estimates are shown for adults, ages 20–69, and are weighted. Prevalence rates are age-standardized to the 2000 Census population.

Figure 2.2—Trends in Obesity, Overweight, and Normal Weight Distributions in California and the Rest of the United States, 1990–2003, by Sex

California men and women had obesity rates of around 10 percent in 1990. By 2003 that rate had increased to about 23 percent for men and 22 percent for women. Thus, over this 13-year time period, the share of men and women who could be considered medically obese in the state more than doubled. Although the trends in rising obesity rates for men and women are largely similar, men are notably much more likely to be overweight than women. For both men and women, and for California and the rest of the United States, the proportion of individuals within the normal weight for height status ranges has steadily diminished over time. Underweight rates (not shown) remained relatively stable over this time period across the state and the nation, hovering around less than 2 percent in any given year.

What Accounts for the Trends in Rising Obesity Rates?

The steady escalation of obesity rates and average BMI documented for California and the nation has been corroborated in many studies. However, explaining the timing of increased obesity rates, and why obesity continues to grow, are questions that are not well understood (Chou, Grossman, and Saffer, 2004).[6] In fact, the rising weight gain across the country may seem paradoxical given Americans' emphasis on "health consciousness," as manifested by the proliferation of health clubs, diet industries, exercise gear, and specialty health foods (Taubes, 1998).

Some researchers have drawn parallels in obesity trends to larger societal changes that have occurred over the past few decades. For instance, Lackdawalla, Philipson, and Bhattacharya (2005) argue that technological innovations, particularly greater efficiency in agricultural production, have lowered food prices while raising the costs of energy expenditure through shifts to more sedentary work and household activities, thereby increasing incentives to be overweight. The rise of convenience and prepackaged foods and the growth of fast-food industries have meant that Americans have much more variety in food

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[6]A review report issued by the World Health Organization (2004) noted that BMI and obesity prevalence have also increased over the years in other countries (both developed and developing), leading some to describe obesity as a global problem.

choices. Convenience foods are relatively easy to mass-produce, are therefore inexpensive (Chou, Grossman, and Saffer, 2004; Cutler, Glaeser, and Shapiro, 2003), and are heavily marketed and advertised to consumers (Nestle, 2002). Moreover, they are attractive because they save both the time and the labor of food preparation (Cutler, Glaeser, and Shapiro, 2003). At the same time, they are often dense in calories and tend to offer little in the way of nutritional benefits. It appears that a greater share of families' food budget is spent on food consumed outside the home than was the case in earlier time periods (Clauson, 1999), and portion sizes for food sold for immediate consumption (e.g., through takeout places, fast-food outlets, and chain restaurants) often far exceed U.S. Department of Agriculture standards (Young and Nestle, 2002). Although one must be careful in inferring causality between these changes and analogous increases in overweight and obesity, recent estimates suggest that the average American in 2000 consumed about 300 calories more daily than in 1985 (Putnam, Allshouse, and Kantar, 2002).

Transportation choices, and particularly car use, may also be a contributing factor. As car use has become much more a part of how individuals get from one place to another, walking and biking (which are, of course, methods of caloric expenditure) have become rarer forms of daily transport (Cutler, Glaeser, and Shapiro, 2003; Frank, Andresen, and Schmid, 2004). These changes in daily forms of transportation and commuting activity have been linked to larger transformations in both suburban and urban environments, including transit availability, population density, land mix use (e.g., distributions of residences, workplaces, and businesses), and street characteristics (e.g., availability of sidewalks and interconnected streets). Some have argued that these alterations in the landscape, including greater sprawl, have helped to promote more sedentary lifestyles (Berrigan and Troiano, 2002; Frumkin, 2002).

Others have noted that changes in leisure time activities, such as increased television viewing and videogame playing (among children and young adults), may have contributed to the rise in obesity (Gortmaker et al., 1996). There have also been changes to the average American family structure; more women have entered the labor force (Anderson, Butcher, and Levine, 2003). These shifts, in turn, have changed the typical food practices of families, leading to greater reliance on packaged or preprocessed foods and restaurants or takeout services for meals. Researchers have speculated that all of these factors, and most likely many others, are associated with increased caloric intake and reduced energy expenditure for many Americans, resulting in greater obesity prevalence.

Summary

Obesity rates have risen in California, more than doubling for both men and women from 1990 to 2003. Since the trends in California are largely parallel to those in the rest of the country, it seems reasonable to conclude that obesity constitutes not just a national public health concern but one that is equally relevant for the state. Estimates from the BRFSS illustrate that average BMIs have increased noticeably, so that the average California man or woman in 2003 was about 12 to 15 pounds heavier than the average man or woman in 1990, respectively. This general trend, however, masks important disparities in obesity that exist by race, ethnicity, and socioeconomic status. In the next chapter, we describe and examine these disparities in more detail.

3. Individual Characteristics and Obesity

In the previous chapter, we demonstrated that obesity prevalence rates have risen for both men and women, adjusting for age differences. This finding is consistent with previous research using national-level data (Flegal et al., 1998, 2002). This overall trend, however, masks a considerable amount of variation among different population groups. Of particular concern are the notable racial/ethnic differences in BMI and obesity that we describe in this chapter and that have been documented at the national level. Here, we examine these racial and ethnic disparities in body mass in detail, using recent data from the 2003 California Health Interview Survey, a representative, statewide health study.

As noted above, understanding the factors that predict high BMI and that account for racial/ethnic disparities are important objectives that can help health promotion and prevention efforts. This chapter explores whether known correlates of obesity, including socioeconomic status and health behaviors, may explain the observed racial/ethnic differences found among California adults. We then examine how various risk factors operate among different racial/ethnic groups and find that although some personal characteristics, such as education, are strong determinants of BMI for most groups, the relationship between other personal characteristics and BMI differs across racial/ethnic groups. Effective policy interventions designed to prevent or to manage obesity are largely contingent on understanding the complex processes that determine high body mass, and these findings underscore the importance of taking a multifaceted approach to obesity prevention.

Racial and Ethnic Disparities in BMI and Obesity

It is well-documented that certain nonwhite groups, particularly non-Hispanic blacks, have poorer health than non-Hispanic whites across a broad range of health issues. However, Hispanics tend to have better health profiles and lower mortality risk than whites, although this pattern varies by nativity status (Johnson and Hayes, 2004).[1] Here, we examine how BMI and obesity differ by race/ethnicity.

Figure 3.1 displays how average BMI varies by racial/ethnic background and sex, after accounting for age.[2] We focus on four main racial/ethnic groups: non-Hispanic whites, non-Hispanic blacks, Hispanics, and non-Hispanic Asians.[3] The disadvantageous higher weight-for-height among Hispanics in California is quite striking, and we too find, in accordance with numerous prior studies, higher BMI levels among blacks in California. For instance, the average 5'10" tall black man in California weighs close to 200 pounds, or has an average BMI of around 28. We also find that the average Hispanic man in California has a notably high and similar BMI of about 28. The average 5'10" tall white man has a slightly lower average BMI of 27 and weighs

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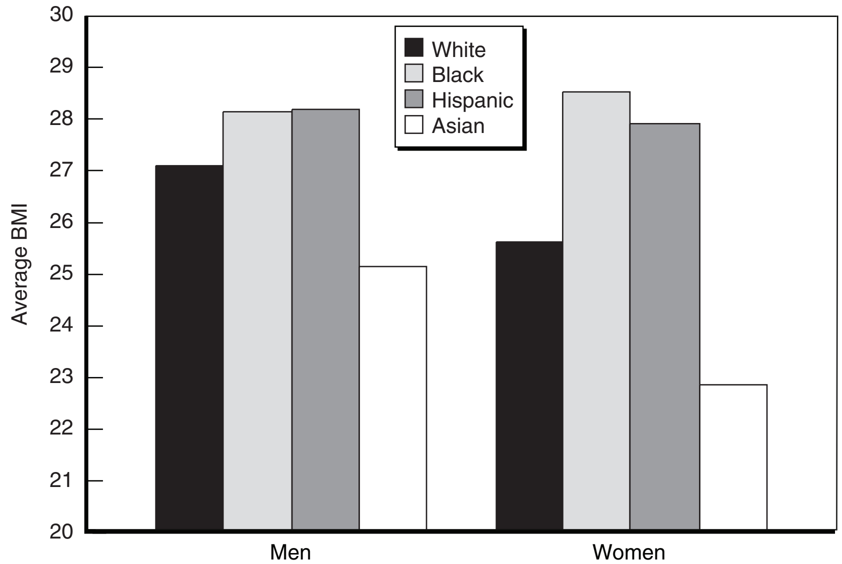
[1]Below, we discuss how nativity status, ethnic origin/identity, and other measures of acculturation relate to obesity risk among Hispanics and Asians.

[2]Controlling for age and age squared helps account for the fact that the racial/ethnic groups in the CHIS differ in their age distributions. For example, Hispanics as a group tend to have an age distribution that is younger than that of whites. As discussed in Chapter 2, BMI tends to increase with age and then downturn slightly at the older ages. Adding an age squared term allows us to adjust for the nonlinear relationship between age and BMI. Estimates of average BMI or obesity prevalence for racial/ethnic and sex-specific groups that do not control for age differences that exist across these population groups may be misleading.

[3]Although the CHIS has information on other racial/ethnic groups including Native American/Alaskan Natives, Pacific Islanders, and other single-race and multiracial/ethnic individuals, the sample sizes were often inadequate for some of these groups to produce reliable estimates. Because the "other" category and multiracial groups (those who identify with two or more racial groups) consist of individuals from various and sometimes unknown backgrounds, we have chosen not to display these results. Throughout the report, we refer to non-Hispanic whites as whites, non-Hispanic blacks as blacks, and non-Hispanic Asians as Asians.



SOURCE: Author's calculation using the 2003 CHIS.

NOTES: The figure shows the predicted average BMI for the major racial/ethnic groups, after controlling for age differences. Estimates are weighted.

Figure 3.1

Figure 3.1—Average BMI Among California Adults, 2003, by Race/Ethnicity and Sex

about 188 pounds, which is squarely in the overweight classification. The average Asian 5'10" tall man in California is lighter, at 174 pounds.

Looking at the bars for women in Figure 3.1, we see that the gap in average BMI for blacks and Hispanics relative to whites is sizable. The varying body mass levels comparing white to black and Hispanic women translate to a 14 to 19 pound weight difference, depending on height. That is, the average 5'4" tall white woman in California weighs 149 pounds, the average 5'4" tall Hispanic woman weighs 163 pounds, and the average 5'4" tall black woman weighs 166 pounds. Asian women, as is the case for men, have notably lower BMIs, such that a 5'4" tall Asian woman in California weighs about 133 pounds.[4]

[4]The differences in BMI found between the various racial/ethnic groups (adjusting for age and age squared) were tested for statistical significance (findings are considered

As was seen in Chapter 2, women generally have more advantageous BMI profiles than men. This pattern, however, does not hold true for blacks or Hispanics. Hispanic women and men have very similar average BMIs; black women have a slightly higher average BMI than black men. The sex and racial/ethnic disparities shown here have been documented in numerous other studies (Chang and Christakis, 2005; Flegal et al., 2002), with the exception of the results for Asians.[5]

As noted in Chapter 2, it is also informative to see how groups fall within BMI weight classifications. Figure 3.2 illustrates the percentage distributions of BMI categories (underweight, normal weight, overweight, and obese) by sex and race/ethnicity. As with average BMI, there are clear disadvantages in the patterning of obesity risk by racial/ethnic background. Black men and women have a higher concentration of obesity than white men and women, respectively, and they also have significantly greater overweight prevalence. As the previous findings would suggest, more black women can be considered obese than adults from any other sex and racial/ethnic group (prevalence rate = 31%). Black men have a similar obesity prevalence rate of about 30 percent. Hispanic women also have considerably high obesity rates of about 30 percent, controlling for age, as do Hispanic men (28%). Only for white women, Asian men, and Asian women do we see majorities fall within the normal weight category.

These disparities are of concern and may be related to a number of other factors that are correlated with both race/ethnicity and BMI. Before we discuss what might explain racial/ethnic differences, we first describe the role that these characteristics, including socioeconomic

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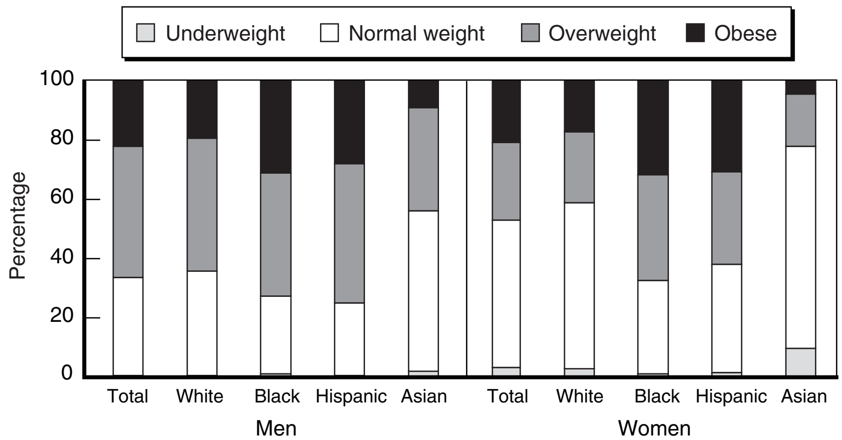
significant at the 5 percent level or less). For men, the differences between whites compared to Asians, blacks, and Hispanics are significant. Asian men also have significantly lower BMIs than the other racial/ethnic groups shown in Figure 3.1. Black and Hispanic men, however, are not significantly different from one another in average BMI (adjusting for age and age squared). For women, whites have significantly lower BMI than blacks and Hispanics and significantly higher BMI than Asians. The difference in BMI between black and Hispanic women, although small in magnitude, is statistically significant. Similar to Asian men, Asian women have significantly lower BMI than the other racial/ethnic groups.

[5]Most studies of obesity or BMI do not report results for Asians, often because of the lack of data or small samples. However, a recent study by Goel et al. (2004) shows obesity rates for Asians that are lower than those for other racial/ethnic groups.



SOURCE: Author's calculation using the 2003 CHIS.

NOTES: The figure shows the age-adjusted prevalence of underweight, normal weight, overweight, and obese weight for men and women, total, and for each racial/ethnic and sex group. Estimates are weighted. Note that the estimates for underweight are based on small numbers of observations for men, black women, and Hispanic women. Estimates for obesity are also based on a small number of cases for Asian women.

Figure 3.2—Percentage of Adults Within BMI Weight Classifications, 2003, by Race/Ethnicity and Sex

status and health behavior, may play independently of race/ethnicity in determining BMI.

The Role of Socioeconomic Status

Socioeconomic status (SES) has been linked to numerous health conditions (Adler and Newman, 2002; Williams and Collins, 1995), and obesity is no exception. Prior research has consistently found that education and income, common indicators of SES, are important correlates of obesity—although the magnitude or size of the associations may vary by race/ethnicity or sex (Ross and Mirowsky, 1983; Sundquist and Johansson, 1998; Zhang and Wang, 2004). SES may be related to BMI in various ways. People with higher incomes often have more access to resources and can better afford services and goods (e.g., gym memberships and healthier foods) that promote healthy weight maintenance than can those on limited incomes. Individuals with more material resources may also live in neighborhoods that are lower in crime and have better pedestrian and traffic safety, which in turn may be related to higher physical activity levels (Yen and Kaplan, 1998).

Although the effects of income on obesity are somewhat mixed, educational attainment is perhaps one of the most important factors for understanding variation in BMI.[6] Education matters, not only through its relationship to income but also because it may indicate increased awareness about the health consequences of obesity and the health benefits of exercise, dietary guidelines, and other health-related behaviors. Sociologists of health have further suggested that SES matters through social norms that may be shared and reinforced among informal networks (e.g., one's circle of friends, family, and acquaintances).[7]

The Role of Behavior

Health-related behaviors, also known as lifestyle factors, are important determinants of health status and also help explain health disparities. Obesity is related to a number of behaviors and the two most important include physical activity levels and dietary intake (U.S. Department of Health and Human Services, 2001).[8] As noted in Chapter 2, these factors are two sides of the caloric energy intake/output coin and are ultimately the drivers of weight gain, loss, and maintenance.

Other health risk behaviors, such as smoking or problem drinking, impose different health risks on individuals (Ross, 2000). Although not as proximate as eating or physical activity, some of these other behaviors

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[6]Sobal and Stunkard (1989) reviewed about 150 studies that examined the relationship between SES and obesity and concluded that most research evidence confirms that lower SES is related to greater obesity risk. Ball and Crawford (2005) provide a more recent review, examining weight gain over time and SES. They concluded that, particularly when SES is measured by education, individuals with low SES are at greater risk of weight gain over time than are their higher SES counterparts.

[7]See Pescosolido (1992) for a discussion of the role of social networks on health. Network ties often cross social class and other boundaries but, in general, they are relatively homogeneous in terms of background characteristics such as race/ethnicity, age, nativity, and socioeconomic indicators, including educational attainment.

[8]Obtaining detailed information on caloric intake is notoriously hard to collect and has questionable accuracy (Cutler, Glaeser, and Shapiro, 2003). Nonetheless, we would ideally have liked to include some measure of dietary habits in our analyses. However, this information is unavailable in the 2003 CHIS.

may be related to obesity. For instance, a study using longitudinal data found that although smoking was associated with lower BMI, quitting smoking was associated with weight gain for men and women (Sundquist and Johansson, 1998).[9] Chou, Grossman, and Saffer (2004) found that higher cigarette prices, which are related to lower smoking rates, were associated with rising obesity prevalence from the mid-1980s to 2000. A recent analysis, however, did not find evidence to support a large weight gain effect from smoking cessation trends (Gruber and Frakes, 2006). There is less research regarding alcohol use and obesity. One could speculate that drinking regularly or heavily may be associated with higher BMI because alcohol is calorie dense and is metabolized by the body in ways that promote fat storage (Arif and Rohrer, 2005). On the other hand, a recent study showed that moderate drinkers actually had lower odds of obesity than those who reported no alcoholic consumption, although researchers do not fully understand why these associations exist (Arif and Rohrer, 2005).

What Explains Racial/Ethnic Differences in Obesity?

Because racial/ethnic groups have different socioeconomic, demographic, and behavioral profiles (Reyes, 2001), it is important to consider the role of such characteristics when examining racial/ethnic disparities in obesity risk. For example, Hispanics in California, who are primarily of Mexican origin, have lower educational attainment and higher poverty concentrations than other groups. Blacks, too, have higher poverty rates than whites and more than a third do not have schooling beyond high school. Blacks are more likely than other groups to report no walking. Whites, however, appear to have less favorable behavioral profiles.[10] They have higher active smoking rates and are

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[9]It has been argued that this finding may in part be because nicotine acts as an appetite suppressant and, perhaps because of withdrawal, people who stop smoking substitute cigarette cravings with increased food intake (Chou, Grossman, and Saffer, 2004).

[10]Although the poorer health behavioral profile of whites compared to the other racial/ethnic groups may seem surprising given their more favorable health outcomes, some research has shown that whites are actually more likely to engage in risky behaviors. White women, for example, have higher prenatal smoking rates than black or Hispanic

more likely than Hispanics, blacks, or Asians to report alcohol consumption above the recommended limit.[11] Thus, the racial and ethnic differences shown in Figures 3.1 and 3.2 may be explained by differing SES or behavioral profiles (for the full array of socioeconomic, demographic, and behavioral characteristics we considered, please see Appendix Table A.1). We examine whether this is the case below, when we look at differences between blacks, Hispanics, and Asians relative to whites while simultaneously accounting for multiple characteristics.[12]

Figure 3.3 shows differences in BMI for blacks, Hispanics, and Asians in comparison to whites, after adjusting for some of the characteristics described above; here, white men have a baseline BMI of 27 and white women have a baseline BMI of 25.6.[13] As we can see, the racial/ethnic disparities are starkest when we examine the results for women, although the patterns are similar for men. Other research has documented a similar pattern of greater variability of racial/ethnic differences in BMI among women than among men, although there is no clear understanding why these patterns exist (Zhang and Wang, 2004).

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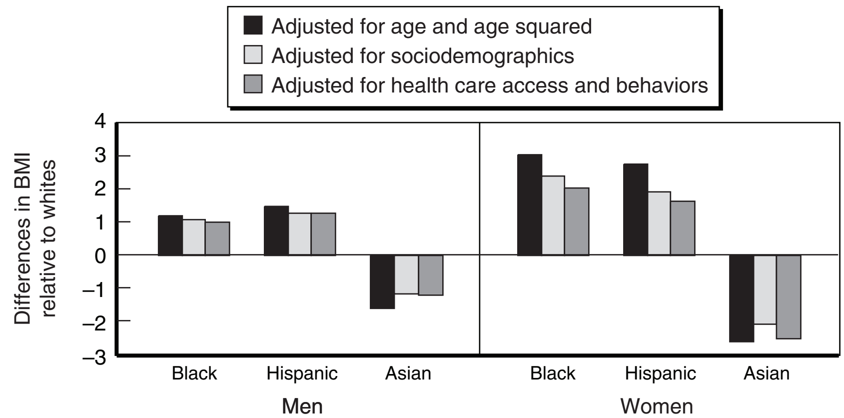
women (Beck et al., 2002). Other health risk behaviors, such as drug use, were not asked in the 2003 CHIS, so we have chosen to examine smoking and alcohol consumption. We also examined binge drinking as an alternative to average alcohol consumption and found no association with obesity, thus we did not include a binge drinking measure in our examinations of BMI.

[11]The recommended limit for alcohol intake is two drinks a day for men and one drink a day for women (U.S. Department of Health and Human Services, 2000).

[12]We conducted two types of statistical analyses for this chapter. One analysis treated BMI as a linear variable and we estimated coefficients from ordinary least squares (OLS) regressions. Another set of analyses used logistic regression models in which obesity (as a dichotomous indicator) was our outcome of interest. Appendix D shows the results from the full OLS models for men and women. The results and conclusions obtained from the logistic regression models were largely similar to the OLS results. Therefore, we do not show these estimates.

[13]These adjusted differences come from coefficients obtained from multivariate linear regression (OLS) models where BMI was our outcome. For full OLS regression results, please see Appendix Tables D.1 and D.2.



SOURCE: Author's calculation using the 2003 CHIS.

NOTES: The figure shows the difference in BMI for adults ages 20–69, adjusted for various characteristics. The characteristics include age (and age squared), other sociodemographic characteristics (nativity, marital status, highest educational attainment, poverty level status, and employment), health care access and use (current insurance and type of regular source of health care), and behaviors (smoking, drinking, and walking). Estimates are weighted. All estimates are significantly different from whites at the 5 percent level or less.

Figure 3.3—Differences in BMI, Adjusted for Personal Characteristics, by Race/Ethnicity and Sex

After adjusting for differences in SES, other demographic factors, and behaviors, we find that the black-white and Hispanic-white disparities in BMI for women still remain sizable and are highly significant. Yet accounting for socioeconomic and behavioral characteristics does attenuate the differences somewhat. When adjusting only for age (and age squared), the difference in BMI between Hispanic and white women was 2.8 body mass index points or about 17 pounds for a 5'4" tall woman. After adjusting for all personal characteristics, that difference was reduced to 1.7 points, meaning that SES, behaviors, and our other controls explained about 39 percent of the Hispanic-white gap among women. These findings suggest that although some of the racial/ethnic disparities in BMI are driven by the varying socioeconomic and behavioral profiles of different racial/ethnic groups, a substantial part cannot be accounted for by these factors.

Results from Models Stratified by Race and Ethnicity

Combining the racial/ethnic groups, as was done in the results shown above, may mask some important variation in the relationships between BMI and the socioeconomic and behavioral characteristics we consider. Therefore, we also estimated models separately for each racial/ethnic group.[14] Doing so allows us to see how correlates of high BMI matter for different sociodemographic groups and may bring potentially important insight for obesity prevention design and interventions. For instance, if low education and low income are similarly associated with greater obesity risk across all racial/ethnic groups, this finding would suggest that targeting education and prevention programs generally toward those with lower SES may be important. If the relationship between SES and BMI is more pronounced for some racial/ethnic groups, this finding may suggest that focusing efforts on creating culturally and socioeconomically sensitive approaches to obesity prevention could be fruitful.

Figure 3.4 shows our results, focusing on two SES characteristics (educational attainment and poverty status) and two important behavioral correlates of BMI (smoking and walking).[15] For whites, we see that education, income, smoking, and walking are all important for understanding BMI differences. Moreover, these factors are related to BMI in ways that we would expect based on what is known in the

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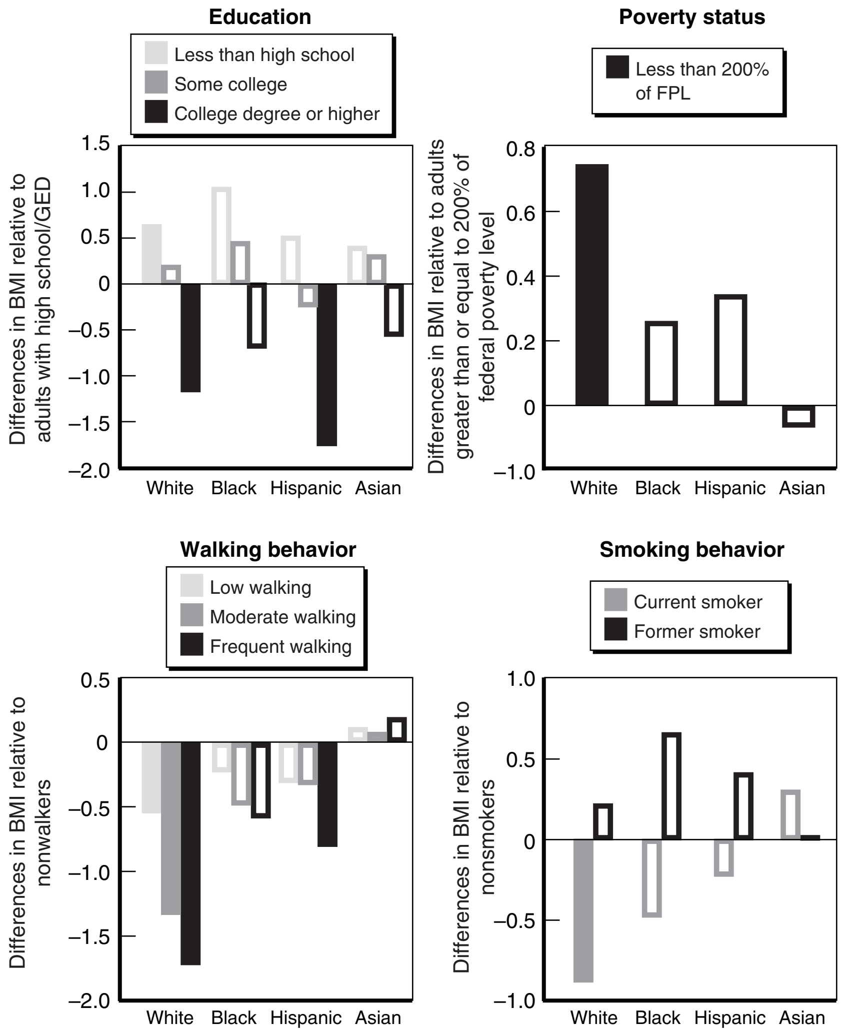
[14]In these models, we have chosen to pool or combine men and women for each racial/ethnic group and to include a control indicator for sex. Sex interactions were tested with the other characteristics (e.g., education, poverty, smoking, and walking) for each race/ethnic group and did not significantly improve model fit, although the inverse relationship between having less than a high school education and higher BMI (relative to individuals with a high school diploma/GED) appears to be slightly stronger for women than for men among whites.

[15]The other characteristics, apart from sex differences discussed above, did not differ substantially across racial/ethnic groups. Note that our other main control characteristics included labor-force participation, drinking behavior, and measures of health care access (measured by health care insurance status and type of regular source of health care). These mattered little for understanding differences within or across racial/ethnic groups. We therefore do not discuss these findings here.



SOURCE: Author's calculation using the 2003 CHIS.

NOTES: The figure shows the differences in BMI found among whites, blacks, Hispanics, and Asians for two socioeconomic characteristics (education and poverty), smoking, and walking. Estimates are weighted and were obtained from OLS models conducted separately for whites, blacks, Hispanics, and Asians. Estimates shown adjust for all other personal characteristics. Solid bars denote that the difference relative to the reference group for each characteristic is statistically significant at the 5 percent level or less.

Figure 3.4—Relationship Between SES and Behavioral Characteristics and BMI for Each Racial/Ethnic Group

literature about obesity risk factors. For example, white Californians who live below 200 percent of the federal poverty level thresholds have significantly higher BMIs than those who live above that threshold.[16] Not unexpectedly, greater frequency of walking is associated with lower BMI among whites. We also see a sizable relationship between smoking and lower BMI relative to nonsmokers, whereby white adult smokers have significantly lower BMIs than white adults who do not smoke. However, these same factors do not go very far in helping us understand BMI among blacks, Hispanics, and Asians, and the strengths of the relationships, in general, are notably smaller than for whites.

For both Hispanics and whites, higher education, particularly at the college level or higher, is strongly associated with lower BMI compared to Hispanics and whites with a high school diploma. However, poverty status, walking, and smoking are less important for explaining variation in BMI among Hispanics than they are for whites. Similarly, for blacks, although the associations go in the expected directions, education, poverty, and walking appear to be less important in predicting BMI. Among blacks, being a former smoker is associated with a BMI 0.65 point higher relative to nonsmokers (however, this estimate is not statistically significant), whereas for whites that association was an increase in BMI of only 0.2 point. For Asians, none of these characteristics hold sizable or significant associations with BMI, perhaps because the variation in BMI for Asians is smaller than that for whites, Hispanics, and blacks.[17]

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[16]For example, in 2003, a family of four with an annual household income of $18,400 or less would be living at or below 100 percent of the federal poverty level. A four-person family with an income of $36,800 would be living at 200 percent of the federal poverty level.

[17]Our inability to detect statistically significant results for some of the characteristics shown in Figure 3.4 for blacks, Hispanics, and Asians may also be due to sample size issues, since our white sample is larger than the other racial/ethnic groups. We conducted model comparison tests (Chow tests), which allow us to assess whether the sets of regression coefficients are equal for whites compared to blacks, whites compared to Hispanics, and whites compared to Asians. Results from this exercise reveal that they are not equal. We also tested whether, for each characteristic shown above, we could say with statistical confidence that the size of the association (i.e., the regression coefficients) was the same for blacks compared to whites, Hispanics compared to whites, and Asians compared to whites. Using F-test statistics, we can be confident that the associations

The Role of Acculturation Among Hispanics and Asians

As noted above, SES and behavioral characteristics are strongly associated with BMI, but the strength of those relationships seems to vary by racial/ethnic background. Among Hispanics and Asians, additional characteristics are important in understanding BMI and obesity. The most notable characteristic is immigrant status and, among immigrants, length of residency in the United States.

A large body of literature has documented a "Hispanic health paradox." This term embodies the fact that Hispanics, particularly Mexicans, tend to have better health outcomes than whites even though they have more disadvantaged SES profiles (Markides and Coreil, 1986). Other research has further shown that over time in the United States, the superior health advantage of Hispanics, noted in the beginning of this chapter, diminishes.[18] Some have argued that this is due to the adoption of health-damaging behaviors and, conversely, the loss of health-protecting behaviors that tend to be more common among recent immigrants. This pattern has been deemed a process of "negative acculturation" to U.S. norms.

The estimates shown in Figure 3.5 account for socioeconomic status, behaviors, and other correlates of BMI and length of time in the United States.[19] These results illustrate that for Hispanics, there does indeed appear to be a significant relationship between higher BMI and longer residency in this country.[20] This finding tentatively suggests that there

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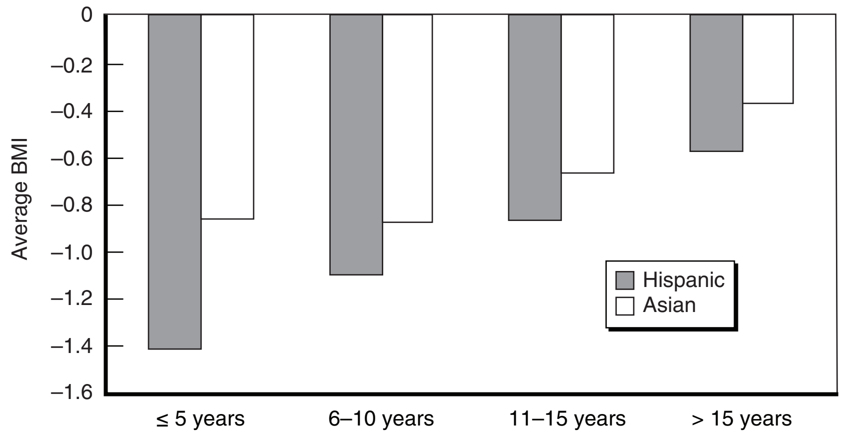
between BMI and poverty status, smoking, and walking were not the same for Asians compared to whites (at a significance level of 5 percent or less). For blacks and Hispanics, differences with whites were not statistically significant at the 5 percent level, except for the association between walking behavior and BMI for blacks and the smoking behavior differences between Hispanics and whites.

[18]The higher obesity rates and average BMI of Hispanic men and women when compared to whites, as shown above, would seem to contradict this health advantage.

[19]In earlier analyses, controls were also added for citizenship and documentation status. These measures were not associated with the outcome and did not change our findings, thus we did not include them in our adjustments.

[20]When we examined the relationship between BMI and length of U.S. residency for both Hispanics and Asians without adding controls for socioeconomic and behavioral



SOURCE: Author's calculation using the 2003 CHIS.

NOTES: The figure shows the difference in BMI by length of residence in the United States for Hispanic and Asian immigrants relative to U.S.-born Hispanics and U.S.-born Asians, respectively. These differences are adjusted for ethnic origin, other sociodemographic characteristics, health care use, and behaviors. Estimates are weighted. All estimates are significantly different from that of U.S.-born counterparts at the 5 percent level or less.

Figure 3.5—Relationship Between Length of Time in the United States and BMI Among Hispanics and Asians

may be a pattern of health deterioration over time, although causality cannot be determined from such cross-sectional data. The baseline BMI for native-born Hispanics (both men and women) is high, an average of 28, which translates to a weight of 195 pounds for a 5'10" tall man and a weight of 163 pounds for a 5'4" tall woman. The BMI profiles of more recent Hispanic immigrants are clearly lower than their native-born counterparts, and these findings are consistent with conclusions from other recent research (Kaplan et al., 2004; Abraido-Lanza, Chao, and Florez, forthcoming). Still, the average BMIs of the most recent immigrant Hispanics are squarely in the overweight range and are close to par with whites (who, again, have lower BMI and obesity prevalence than Hispanics as a whole), suggesting that negative acculturation to "American" norms may be only one part of a more complex story.

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characteristics, the patterns in BMI differences by duration of time are similar to the patterns shown in Figure 3.5.

To our knowledge, very few studies have examined the relationship between acculturation and health among Asians. Although we have noted that Asians have much lower average BMI than the other racial/ethnic groups, the pattern of higher BMI by duration of residency in the United States is true for Asians as well.[21] This may be taken as a sign that the BMI distribution among Asians moves increasingly in the normal range with greater length of time in this country, as opposed to an indication of health deterioration. However, other research has indicated that the negative health risks associated with higher BMI occur at a lower threshold for Asian subgroups than it does for other groups (Choo, 2002), suggesting that there may be cause for concern. Although we cannot say from these data what accounts for the role of duration of U.S. residency in the risk of higher BMI, our findings suggest that there may be something about the U.S. context that is associated with higher weight among immigrant groups, and this appears to be true for both Hispanics and Asians alike.

Summary

Disparities in health among minority groups relative to whites constitute long-standing and significant health policy concerns. The differences in obesity risk that we have documented throughout this chapter illustrate that obesity is yet another example of health disparities along racial/ethnic lines. The findings in this chapter reveal that the differences in BMI between Hispanics and whites and blacks and whites are sizable, particularly for women. Even after considering the role of numerous socioeconomic and behavioral correlates of BMI, we were still

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[21] We also examined differences among Hispanics and Asians by national/ethnic origin. There is some variation by ethnic subgroup (i.e., for Hispanics, we compared Mexicans to Central Americans, South Americans, and other Hispanics; for Asians, we compared Chinese to Japanese, Korean, Filipino, Vietnamese, Southeast Asian/ Cambodian, South Asian, and other Asians). However, generally speaking, we found that BMI was largely similar among these groups. There were a few exceptions: South Americans had lower risk of obesity and lower BMI relative to respondents who identify as Mexican or Mexican American. Vietnamese or Vietnamese Americans have lower BMI relative to Chinese Americans (the majority Asian subgroup in the CHIS). Filipino Americans and South Asian Americans have slightly higher BMI than Chinese Americans.

unable to account fully for these racial/ethnic gaps. We also found that although the known correlates of body mass, including SES and health-related behaviors, were important for understanding BMI differences for whites, they were not as relevant for understanding BMI among blacks, Hispanics, or Asians in California. For Asians and Hispanics, it appears that recent immigrants had more favorable BMIs than their U.S.-born counterparts, suggesting that acculturation to the United States may increase obesity risk. Taken together, these findings imply that obesity risk is a multifaceted problem, with no clear or simple solution. These results also suggest a need to go beyond standard individual-level explanations. We turn to this issue in the next chapter, where we address the role of the neighborhood context in high BMI.

4. Neighborhood Context and Obesity

Many health researchers have long argued that to fully understand the determinants of health, one must consider factors beyond those of the individual and take into account the individual's residential and social environment.[1] Namely, is there something about one's neighborhood that promotes a healthier lifestyle or, conversely, hinders engagement in healthier practices? The idea that aspects of the neighborhood environment help explain obesity risk has garnered considerable popularity in recent years (Hill and Peters, 1998) but has not been fully explicated empirically. This chapter contributes to this dialogue by examining in detail the relationship between neighborhood context and obesity.

In Chapter 3, we showed how various individual characteristics play a role in predicting high BMI. Because we could not explain a significant part of the racial/ethnic disparities in BMI when we focused on individual characteristics alone, we now investigate neighborhood characteristics to help explain these considerable differences. Specifically, we are interested in the following questions: (1) What is it about neighborhoods that mater for BMI? (2) Do neighborhoods help explain racial/ethnic differences in BMI? We incorporate several objective measures that tap into different aspects of neighborhood environments that may be important for understanding BMI and that vary across California residents.[2]

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[1]See Kawachi and Berkman (2003), Robert (1999), and Ross (2000) for a discussion of why neighborhoods may matter for health behaviors or outcomes.

[2]For more on the methodology used to estimate relationships between neighborhoods and BMI, please see Appendix B, which also describes our measures of neighborhood context.

It is beyond the scope of our data to establish causal relationships between neighborhood characteristics and BMI. Because individuals choose to live in certain neighborhoods based on a number of diverse criteria, ranging from neighborhood safety, community infrastructure, school quality, housing and rental prices, and access to neighborhood resources, it is very difficult to disentangle the causal relationship between such features of the neighborhood environment and individual outcomes. For (an extreme) example, if an obese individual prioritizes proximity to fast-food establishments in choosing where to live, we cannot say that the concentration of such establishments caused that individual to be obese. Despite the fact that causal relations cannot be established, addressing the role of neighborhoods is important as both a research and a policy issue. Even though individuals choose different neighborhood environments, if they wish to change their behavior, then understanding whether certain aspects of neighborhoods hinder or promote such change can inform current debates regarding community design, safety, and the local food environment. As we shall see, neighborhoods do matter to some extent, particularly for certain groups. Although it is difficult to say for certain which neighborhood characteristics are most important in terms of understanding obesity, our findings suggest that framing and designing policy interventions that focus solely on individual behavioral modification alone may be of limited efficacy without also addressing how neighborhood environments make such behavioral changes more or less feasible.

Why Might Neighborhoods Matter?

There are some indications in the literature that certain neighborhood aspects may be related to obesity. Much of this research has taken the neighborhood (defined at numerous aggregations) as the unit of analysis and focused on variation in access to resources by neighborhood characteristics. Neighborhoods can be defined at various levels, or sizes, but most studies typically define a neighborhood at the Census tract level. For several reasons, in this report we define neighborhoods at the zip code tabulation area (ZCTA) level (an aggregation, parallel to zip codes, comprising an average of about 11 Census tracts). First, some of the objective measures of neighborhood characteristics that we collected are at the zip code level and are difficult to disaggregate to the Census tract level. Also, one could argue that some of the measures we are interested in (such as the concentration of grocery stores and convenience stores) matter more at a larger area level than at a smaller geography, such as Census tracts or block groups.[3] At the same time, our aggregation may arguably be too large to capture associations between neighborhoods and weight status and we proceed with this caveat.[4]

A number of studies have looked at the relationships between neighborhood sociodemographic characteristics and aspects of the local food environment to determine which neighborhood characteristics might be important. Defining neighborhoods at the zip code level, Morland et al. (2002) found that low-income neighborhoods had fewer food stores and supermarkets than did areas with higher median incomes. Access to supermarkets may be important because they offer a greater variety of fruits, vegetables, and other food choices than, for example, convenience stores. The authors also found that supermarkets were much more prevalent (approximately four times so) in neighborhoods that were predominantly white than in neighborhoods with a higher concentration of black residents. Another study found that fast-food outlet concentration was significantly higher in low-SES and predominantly black neighborhoods (Block, Scribner, and DeSalvo, 2004). This line of research suggests that poor and nonwhite neighborhoods have less access to healthier food options and resources than other neighborhoods, although it should also be noted that the concentration of food stores and restaurants in certain neighborhoods may be driven by demand among residents. The studies reviewed above

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[3]In addition, we also note that although we had access to 2000 Census tract identifiers for CHIS respondents, there was often only one or two observations in a tract, making it cumbersome to conduct statistical analyses and uninformative to run neighborhood fixed-effects models, discussed later in the chapter.

[4]Robustness checks were run, in which rural ZCTAs, which tend to comprise larger numbers of Census tracts than smaller, urban ZCTAs, were excluded from our analyses. The results from this exercise revealed similar conclusions to the results reported in this chapter, suggesting that ZCTAs may be reasonable approximations of local conditions, despite the varying sizes of ZCTAs in California.

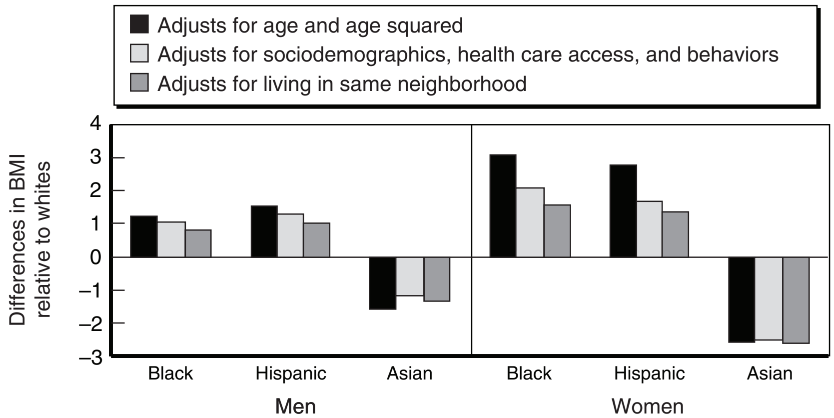
did not link these neighborhood characteristics to individual risk of obesity.

In an examination of childhood obesity, Sturm and Datar (2005) merged individual data and Metropolitan Statistical Area (MSA) contextual measures to examine the relative contributions of MSA environment, family, and child characteristics on BMI. The authors found no statistical relationships between food access or restaurant outlet concentration and BMI. However, they did find that higher local food prices for fruits and vegetables were associated with an increase in BMI. In a study of health behaviors and neighborhood context (using Census tract characteristics), Ross (2000) found that residents in poor neighborhoods were actually more likely than those in nonpoor neighborhoods to report walking, independent of their individual SES, but no associations were found between neighborhood characteristics and more strenuous forms of exercise.[5] More recent studies have also addressed the role of the neighborhood on the risk of adult obesity (Boardman et al., 2005; Robert and Reither, 2004). This research has generally found that although community socioeconomic disadvantage was significantly related to higher obesity risk, individual SES mattered more for explaining black-white differences. Thus, the evidence on the role of neighborhoods and BMI, and how much neighborhood context helps explain racial/ethnic differences, is somewhat mixed.

Do Neighborhoods Matter for Explaining Racial/ Ethnic Differences in BMI?

Do neighborhoods matter for predicting BMI? Do they help explain racial/ethnic differences that cannot be fully accounted for by looking at individual characteristics alone? The results displayed in Figure 4.1 give insight into these questions. Without adjusting for living in the same

[5]This finding may partly reflect the fact that for many individuals, walking is not only for exercise. Individuals in poor and low-income neighborhoods or with limited economic and transportation resources may walk as their main mode of transport, because other transportation means are not as affordable or available. In addition, more people rent in poorer neighborhoods, which is associated with higher density and community infrastructure that is conducive to walking (Ross and Mirowsky, 2001).



SOURCE: Author's calculation using the 2003 CHIS.

NOTES: The figure shows racial/ethnic differences in BMI relative to whites, adjusted for various factors. Estimates are weighted. The first bar shows racial/ethnic differences that have been adjusted only for age and age squared (and not neighborhoods) for comparative purposes. The second bar adjusts for age (and age squared) and other personal characteristics (such as nativity, education, income, health care access/use, and behavior). The last bar adjusts for all personal characteristics and also for living in the same neighborhood using neighborhood fixed-effects (see Appendix B for a discussion of methods). All estimates are statistically significantly different from those for whites at the 5 percent level.

Figure 4.1—Differences in BMI, Adjusted for Personal Characteristics and Living in the Same Neighborhood, 2003, by Race/Ethnicity and Sex

neighborhood, racial/ethnic differences (shown by the first bar for each racial/ethnic group) are sizable (controlling for age and age squared), especially for women. When we account for other personal characteristics, including individual SES, health care use, and behaviors (seen in the second bar for each racial/ethnic-sex group), the racial/ethnic difference reduces for all groups, particularly when examining black-white and Hispanic-white differences for women. In the last bar for each racial/ethnic group, we further account for neighborhoods (in addition to all individual characteristics), essentially examining racial/ethnic differences in BMI found among respondents who reside in the same neighborhood. We see that neighborhoods do indeed matter, above and beyond personal characteristics, and they help explain part of the black-white and Hispanic-white differences in BMI, especially for women. For instance, adjusting for living in the same neighborhood accounts for an additional 25 percent of the black-white and about 18 percent of the Hispanic-white difference in BMI found among women, even after adjusting for all personal characteristics. Controlling for living in the same neighborhood reduces the black-white and Hispanic-white differences for men but not nearly as much as it does for women, perhaps suggesting that neighborhood context may matter more for understanding racial/ethnic differences in BMI among women than among men. Notably, adjusting for living in the same neighborhood does very little to help us explain the much lower BMI among Asians relative to whites.

It should be noted that even after adjusting for sharing the same neighborhood, we find that many of the predictive individual characteristics described in Chapter 3, including education, poverty, smoking, and walking, are still significantly related to BMI and that their associations with BMI change very little.

The Role of Neighborhood Characteristics

The results shown above tell us that neighborhoods do matter for understanding obesity risk, and living in different neighborhoods can account for some of the observed black-white and Hispanic-white disparities in BMI. These results cannot tell us, however, what it is about neighborhoods that might be related to BMI. We turn to this issue by examining a host of different neighborhood characteristics, drawn from various sources, that we hypothesized might be important for understanding obesity risk. (See Appendix Table B.1 for a list of some of these neighborhood characteristics, the data sources, and information on their construction.)

Our data, from the CHIS, show some variation in the types of neighborhoods that different racial/ethnic groups inhabit. For instance, whites and Asians live in ZCTAs with higher median family income than do blacks or Hispanics. Blacks and Hispanics appear to live in more disadvantaged neighborhoods than whites or Asians, with higher poverty and homicide rates. However, the number of grocery stores and convenience stores per 1,000 residents and the ratio of grocery stores to convenience stores are largely similar across racial/ethnic groups.

Many of the neighborhood measures that we examined were highly correlated with one another. In particular, measures of neighborhood poverty, median income, percentage of households on public assistance, unemployment rates, and low educational attainment among neighborhood residents were strongly associated with each other.[6] Ultimately, we decided to investigate a handful of different measures that tap into various aspects of neighborhoods.

For a measure of socioeconomic disadvantage, we used the percentage of residents (for whom poverty status is determined) living in poverty taken from the 2000 Census. The racial composition of neighborhoods has been linked to a number of health outcomes (e.g., birthweight and cardiovascular disease), and living in predominantly white neighborhoods is associated with better outcomes. Racial composition is measured in our study by the percentage of residents who are white, as this percentage can be seen as an indicator of majority group (e.g., social status) privilege and its related advantages (e.g., access to and mobilization of resources). In addition, the percentage of white residents, more so than the percentage of black, Hispanic, or Asian residents, had more variation among the ZCTAs found in the CHIS.

We also examined whether the neighborhood had a high percentage of adults (age 16 or older) who reported that they usually walked or biked to work. This measure may tap into various elements of neighborhoods that could be related to obesity, including safer community infrastructure and pedestrian accessibility, both of which may be associated with greater physical activity within a neighborhood. However, a higher percentage of walkers/bikers also may indicate neighborhoods where residents do not have access to cars or other forms of vehicular and public transportation, which would make this indicator a proxy of disadvantage.

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[6] One general solution in the literature for incorporating correlated neighborhood measures is to create community or neighborhood indexes that combine or sum several of these characteristics (Robert and Reither, 2004; Robert, 1999) to create one summary measure. These composite indices assume that there is some underlying construct or common factor that each measure jointly taps into. The disadvantage of this approach is that one cannot disentangle how these characteristics operate separately in predicting a particular outcome.

We included the homicide rate for the zip code area as a measure of neighborhood safety and disorder. Because of fear and subsequent social isolation (Klinenberg, 2002), high crime rates may discourage individuals from engaging in activities that would otherwise be beneficial for healthy weight status, such as walking to work or for leisure. Finally, we looked at the average number of grocery (e.g., supermarkets) and convenience stores per 1,000 residents in the ZCTA, as a proxy for the local food environment.

All of the characteristics described above cannot, of course, cause an individual to be obese or to gain weight. Some of these aspects of neighborhood environment may be seen as proxies for community resources, safety, and disorder. These neighborhood characteristics may also tap into broader sociocultural community norms regarding weight-promoting or weight-losing activities. Such neighborhood features, in turn, may help to shape perceived barriers, feasibility, and motivation that individuals associate with engaging in health-promoting activities, such as walking or biking and maintaining a balanced diet.

These measures and their relationship to BMI, adjusting for various individual characteristics, are seen in Table 4.1.

Even after we adjust for individual socioeconomic characteristics and behavioral factors, neighborhood poverty is significantly associated with higher BMI among women. Every 10 percent increase in the percentage of individuals in poverty at the neighborhood level is associated with an increase in BMI of about 0.4 for women. So for a 5’4” tall woman, this increase in neighborhood poverty would be associated with a weight increase of about 2.5 pounds. Although the size of this association is relatively small, this finding is consistent with other recent research that has documented an independent relationship between conditions associated with neighborhood economic disadvantage and higher BMI (Boardman et al., 2005; Robert and Reither, 2004). Although our measure of neighborhood poverty may be less comprehensive than is ideal, living in a poor neighborhood, above and beyond a lack of resources and individual SES, may be an indication of an adult’s cumulative socioeconomic disadvantage, which is associated with higher risk for obesity (James et al., 2006a, 2006b).

Table 4.1

Neighborhood Characteristics and Associated Changes in BMI

Neighborhood Characteristic	BMI of Men	BMI of Women
Homicide rate	+0.111	+0.159
Average number of grocery stores per 1,000 residents	–0.157*	–0.053
Average number of convenience stores per 1,000 residents	+0.203*	+0.090
Percentage white	–0.008**	–0.013**
Percentage below poverty	+0.011	+0.039**
Percentage who walk/bike to work	–0.091**	–0.076**

SOURCE: Author's calculation from merged 2003 CHIS and neighborhood contextual data.

NOTES: This table displays the estimates of our five neighborhood characteristics on BMI, based on models run separately for men and women. We show the estimates obtained when we consider all personal characteristics and the other neighborhood measures. Estimates are based on multilevel, random-effects models that are unweighted (see Appendix B for more on weighting issues in our multilevel random-effects models). A plus sign in front of the estimate denotes that the association between the neighborhood characteristic and BMI is positive. A minus sign before the estimate signifies that the relationship is negative.

*Statistically significant at the 5 percent level or less.

**Statistically significant at the 1 percent level or less.

As for our other measures, we find that for both men and women, living in neighborhoods with a higher percentage of white residents is associated with lower BMI. Taken together with the research reviewed above (documenting greater access to resources and lower fast-food concentration in white neighborhoods), this finding is not surprising. Our measures of the number of grocery and convenience stores per 1,000 residents do not bear statistical relationships to BMI among women, although they do for men. Men who live in neighborhoods with a higher number of convenience stores and lower number of grocery stores have higher BMI than men who live in places where those concentrations are reversed. Living in neighborhoods where more adults walk or bike to work is significantly associated with lower BMI for both men and women. This may indicate a community landscape and infrastructure that is more conducive to such activities, or it may proxy larger social norms that reinforce or encourage an active commute among residents. Although the introduction of neighborhood characteristics does improve the explanatory power of our model, the individual characteristics that we discussed in Chapter 3 continue to be the factors most strongly related to weight.

One question that motivated the analysis in this chapter was whether we could further explain racial/ethnic differences in BMI by adjusting for specific neighborhood characteristics. We found that the black-white and Hispanic-white BMI disparity for both men and women was slightly reduced after adjusting for the neighborhood characteristics shown above, typically by a difference of 0.2 to 0.3. Thus, the neighborhood characteristics that we considered could not account in a sizable way for the observed differences in BMI for blacks, Hispanics, and Asians relative to whites. They do, however, seem to be associated with BMI, above and beyond personal characteristics, even if they cannot fully explain disparities that exist among these groups.

Summary

The findings presented in this chapter suggest that neighborhood context, independent of individual SES and behaviors, may help explain differences in BMI among racial/ethnic groups. However, accounting for specific aspects of the neighborhood environment, such as neighborhood poverty, racial composition, and neighborhood safety (measured by homicide rates), did little to explain these racial/ethnic disparities. This may, in part, reflect the concern that our definition of "neighborhoods" (the zip code tabulation area) may be too broad to adequately detect or capture associations. In addition, the neighborhood characteristics we considered may not be tapping into the aspects of neighborhoods that matter most for understanding obesity risk. Nonetheless, we found that some of these neighborhood characteristics, including poverty rate and racial composition, were associated with BMI independent of individual SES and behavioral characteristics. Among the medically obese Californians surveyed in the 2003 CHIS, about 27 percent (or about 1.2 million) lived in poor neighborhoods, suggesting that designing strategies to address obesity risk in poor neighborhoods may be an important place of emphasis for public health campaigns and interventions.[7] Although some of these findings merit further research and corroboration, our results tentatively suggest that obesity risk may well be a multilevel phenomenon (Robert and Reither, 2004). If the problem of obesity extends beyond that of the individual, policy approaches to addressing obesity may also need to address the role of the neighborhood environment.

[7] A poor neighborhood was defined in this example as a ZCTA with poverty rates of at least 20 percent.

5. Policy Options and Prevention Efforts

In this chapter, we present an overview of the research on obesity prevention efforts and related interventions. Our purpose is to objectively assess and summarize various strategies, outlined in existing programs and earlier research, to inform and aid current public health and policy discussions. Understanding potential prevention options can help health officials in their efforts to address the concerning trend in rising obesity rates and the unequal distribution of obesity risk that this report and others have documented.

Although a number of general studies on obesity prevention exist, a substantial part of this literature consists of "call to action" pieces or reports. In other words, rather than evaluating the efficacy of specific campaigns, policies, or programs, the bulk of these studies present arguments by leading health experts discussing what *should* and *could* be done. For the most part, we will focus our discussion on prior, current, and ongoing prevention efforts and review options that have been or may be considered by various policymakers. We focus on three main themes related to obesity prevention and policy: (1) public education campaigns, using the California Department of Health Services' and National Cancer Institute's 5 A Day campaign as an illustration of such an approach; (2) taxation debates regarding sale taxes on snacks, soda, and other food-related purchases; and (3) community-based and workplace interventions that have taken a localized approach to improve diet and exercise. Most of what we review below is not California-specific, as few published studies focus solely on evaluating California prevention efforts.

Public Health Campaigns

Most strategy recommendations from leading health organizations (e.g., the National Heart, Lung, and Blood Institute and the National Cancer Institute (NCI)) note that attempts to successfully halt the tide of rising obesity rates must include efforts that promote, encourage, and support healthier eating habits and physical activity. The 5 A Day program is an example of a recent, large-scale public health campaign designed to address the role of nutrition on individual and population health. The 5 A Day effort is a national and statewide campaign developed by the California Department of Health Services and adapted by the NCI to encourage people to improve dietary practices—specifically, to promote consumption of fruits and vegetables (at least five servings a day). It was initiated in California in 1988 and introduced nationally in 1991. Since its inception in California, the state has tailored campaigns to focus on children, Hispanic and black communities, and low-income families (California Department of Health Services, 2004; Reed and Karpilow, 2004).

The motivation for the campaign was based on research demonstrating a link between diets rich in fruits and vegetables and reduced risk of certain cancers. A secondary rationale was that increased intake of fruits and vegetables (which are typically low in calories and high in fiber) would also reduce the risk of obesity, diabetes, and cardiovascular disease (Buller et al., 1999). The NCI collaborated with private industry partners, including producers and retailers of vegetables and fruits, to promote the 5 A Day program. The all-volunteer dissemination of the message operated largely via public health awareness ads, advertising in retail markets (e.g., grocery stores), magazines, television, and media releases (e.g., billboards, news ads, and stories).

An evaluation (commissioned by the NCI) found that awareness of the campaign and knowledge about the benefits of diets rich in fruits and vegetables have increased over time.[1] This evaluation also found that the mean number of fruit and vegetable servings consumed by adults increased slightly over the time period of the program's implementation.

[1]For more information on the NCI evaluation, see http://www.cancercontrol.cancer.gov/5ad_exec.html.

The report relied on estimates from the BRFSS and the U.S. Department of Agriculture's Continuing Survey of Food Intake by Individuals (CSFII) to examine mean fruit and vegetable consumption over the period of the inception of the campaign across the country (early to late 1990s).[2] However, evaluation studies such as this, particularly when it comes to media or public awareness campaigns, run into admitted measurement difficulties in regard to population-level behavioral changes (National Cancer Institute, n.d.). The primary reason for caution is that everyone is possibly exposed to a campaign and there is thus no appropriate comparison group. Furthermore, awareness can come from various sources (e.g., doctors, friends, family, and the workplace) and not just the campaign itself. Finally, there may be other reasons for an increase in fruit and vegetable consumption (i.e., food prices and availability). Thus, one cannot say whether an observed increase in fruit and vegetable consumption would still have occurred in the absence of the 5 A Day campaign.

It is important to note that recommending greater consumption of fruits and vegetables and other healthier food options may be a message that has limited relevancy for certain segments of the population. For instance, numerous studies have demonstrated that the average cost of following a recommended diet high in fresh fruits, vegetables, and lean protein is greater than following a diet that is higher in fat, sugar, and processed foods (Drewnowski and Specter, 2004; Drewnowski, 2004; Hill, Sallis, and Peters, 2004; Jetter and Cassady, 2005). Low-income households and individuals tend to purchase more energy-dense foods partly because these foods are relatively inexpensive. Focus group studies of low-income individuals' food choices reveal that higher prices and difficulty in accessing healthier food options may be barriers to those on limited incomes (Shankar and Klassen, 2001).

[2]The BRFSS and the CSFII count different foods as fruits as vegetables and are thus difficult to compare. For example, the CSFII includes fruits and vegetables contained in condiments, candy, potato or other chips, and fried foods. The BRFSS excludes these types of foods in its calculations. Also, although the BRFSS collects basic dietary information, the CSFII is much more detailed in collecting information regarding everyday nutrition, portion sizes, and overall caloric intake.

Although 5 A Day focuses on nutrition education, there has not been a parallel or as widespread a campaign to increase physical activity. The 2005 dietary guidelines, issued every five years by the U.S. Department of Health and Human Services and U.S. Department of Agriculture, has promoted a simple message of "eating less and moving more." In these guidelines, individuals are encouraged to engage in 30 minutes of regular physical activity for most days a week. How well this message has been disseminated is unclear. In California, Governor Schwarzenegger's administration has created a resource guide to promote physical activity as part of a "Get Healthy, California" campaign. The guide also includes a "fitness pass" that gives qualifying high school students a free 30 day membership to a fitness club. This physical activity campaign is too recent in its inception, however, to examine its efficacy.

Taxation

Several researchers have argued that to combat or compensate for unhealthy food environments, state and local governments should implement taxes (e.g., "snack" or "soda" taxes) on foods that are high in calories, fat, and sugar content. Similar to the approach taken with tobacco taxes, the funds generated from these snack or soda taxes could be used to subsidize healthier foods such as fruits and vegetables and to generate funding for obesity prevention and awareness campaigns (Jacobson and Brownell, 2000). However, opponents of such measures have argued that such a tax may be regressive and would penalize those with lower incomes.

Another issue with imposing a food tax is defining what items to tax. That is, what constitutes a "snack"? California's sales tax on snack foods, enacted in 1991, was repealed in 1992 because of ambiguity and disagreement regarding what foods qualified as a snack. After 1992, the snack tax then was limited to soft drink sales. Even so, Jacobson and Brownell (2000) estimated that this tax generated about $220 million for the state, all of which went (and continues to go) into the state's general fund. Several other states, including Arkansas, New York, Tennessee, and West Virginia, have soda or snack taxes in place (Fierro, 2002). However, as with California's soda tax, in most of theses states much (if not all) of the revenues go into general funds and are rarely earmarked for obesity prevention programs.

Efforts to increase or impose soda or snack taxes are often met with heavy opposition by food and soft drink industries, in addition to consumers (Benforado, Hanson, and Yosifon, 2005; Brownell and Horger, 2003).[3] Several states, counties, and cities that implemented such snack or soda taxes have repealed them, and one study argues that these repeals are attributable to pressure and lobbying from soft drink and food manufacturers (Jacobson and Brownell, 2000). To our knowledge, no study has examined the effect that such snack or soda taxes have on obesity and obesity-related behaviors. However, Kuchler, Tegene, and Harris (2004), using simulation models, calculated the potential effects of varying snack tax rates on consumer response. The authors concluded that imposing a relatively low tax rate of 1percent on certain snacks would probably have little effect on dietary practices or obesity-related outcomes but that such a tax would generate a sizable amount of tax revenues. These revenues, in turn, could be channeled into funding nutritional and physical activity informational programs.

Community and Workplace Interventions

Although workplace and community-based interventions that promote health and well-being have a long history, there is little systematic evidence to suggest that these efforts, particularly in regard to obesity risk, have had a measurable, long-term effect on either behaviors or outcomes. Workplace programs, although not widespread, are likely to be a relevant avenue for promoting physical activity and healthier eating habits among adults. Some employers, recognizing the potential long-term effect on worker health and productivity, have encouraged such awareness campaigns (Koplan and Dietz, 1999). Sorenson et al. (1999) reviewed a series of randomized trials in which a mixture of educational and structural changes in workplace environments (e.g.,

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[3]Other scholars outline larger ethical concerns that are hallmark issues in public health. These issues relate to the tradeoff between potential health benefits at the population level from such taxes or other regulations and individual rights and autonomy (Wilson and Thomson, forthcoming).

changes in the types of foods sold in vending machines) were instituted. Employees in workplaces with both an educational/informational component and a structural component were compared to employees who did not experience direct educational efforts. The overall results suggest a modest effect on dietary intake among employees who received both the informational and the structural support, but a sustained effect on workers' BMI was not found several months after the program.

Other research has examined the role of various nutritional and physical activity promotions in both workplaces and communities through pre- and post-intervention comparisons. Although several studies have documented changes in terms of greater health awareness and improvement in health-related behaviors, many of these studies are flawed empirically because they do not have an appropriate reference or control group (i.e., a comparison group that did not receive the intervention). Thus, it is difficult from this research to determine whether the same results would have been observed in the absence of the intervention.

One well-known community-based intervention effort is the Stanford Five-City Project. The overall goal of the project was to take a community-based, intensive approach to reduce cardiovascular disease risk and high BMI among local residents (Farquhar et al., 1990). Although the project was conducted 20 years ago, it is of interest because there were two "treatment" and three "control" or "reference" cities. Over a five-year period, the treatment cities received a coordinated mass media and face-to-face educational intervention campaign that targeted healthy weight regulation or loss through diet and exercise.[4] The control cities received no such educational intervention. Findings from this project revealed that in both treatment and control cities, residents showed movement over time toward becoming more overweight, although the percentage increase in BMI in the control cities was slightly

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[4]The educational program consisted of television campaigns and local radio spots (including Spanish language radio spots) and advertisements promoting better nutrition and the benefits of exercise. Interpersonal education included local classes, seminars, and workshops. Households in the treatment cities were also sent weekly "tip sheets" that described recommended "heart healthy" nutrition strategies (Farquhar et al., 1990; Taylor et al., 1991).

higher than in the cities that received the educational intervention. A cohort analysis revealed no significant difference between treatment and control cities in BMI, although residents' overall cardiovascular disease knowledge was significantly greater in the cities that received the educational intervention than in control communities (Taylor et al., 1991).

Similar studies show mixed results. A more recent, parallel study conducted in Great Britain revealed very comparable findings to the Stanford project. In this case, the authors could not detect an intervention effect on behavior or BMI over and above that of the control group (Tudor-Smith et al., 1998). In contrast, a long-term prevention program conducted in Finland, called the North Karelia Project, has been thought of as an example of a relatively successful community-based intervention approach (Puska, 2002). Begun in the 1970s with the goals of promoting public awareness and reducing the community's high incidence of cardiovascular disease, the project relied on multiple partnerships between local and national authorities, medical experts, the World Health Organization, local media, food retailers, and the agricultural industry. Health statistics (i.e., mortality rate changes from heart disease and overall mortality rates) assessed 25 years after the initial inception period revealed measurable reductions compared to the pre-program years (Puska, 2002). Although the results from this program underscore the potential need for longer-term community-based intervention approaches and evaluations, the generalizability of the study (North Karelia is socioeconomically and racially/ethnically homogeneous) should be viewed with some caution.

Summary

The policy options and program evaluations reviewed above raise some important issues. Many of the programs aimed at improving diet and exercise and reducing obesity risk have not detected a measurable effect on behavior or health outcomes. This may partly be due to the need for both longer-term interventions and longer-term evaluations. When an association has been detected, it is often difficult to say whether that relationship is causal, suggesting the need for more carefully designed studies and interventions. Yet there is some evidence that community-based, work-based, and larger public health campaigns do increase awareness of risk factors and of the benefits of engaging in healthier practices. Ensuring that the promotional message has relevancy and constitutes a feasible behavioral change for diverse populations, however, is an important issue that health officials should consider.

6. Conclusion

Obesity rates have risen markedly in California, much the same way that they have risen for the nation. Although some researchers debate whether obesity constitutes a true "epidemic," most concur that obesity imposes serious risks to individual health. The consequences of these health risks are placed not just on the shoulders of individuals but are borne by family members, employers, the health care system, and, ultimately, the government. Thus, the current high prevalence rates of adult obesity in the state may exact a considerable toll on the public's well-being in the future.

Although obesity has increased across sociodemographic groups, the burden of obesity is not equally concentrated. Using a statewide representative dataset, we have found, as have many others, disparities among racial and ethnic groups in obesity risk in California. The differences in average BMI between blacks and whites and Hispanics and whites are large, and these differences are most striking for women. For example, the disparity between black and Hispanic women relative to white women in California translates to a weight difference of about 14 to 19 pounds, depending on height.

Understanding these disparities and the determinants of high BMI is an important issue that can help in the design and scope of various prevention strategies, including public health education and awareness. We found that part of the racial/ethnic difference was driven by differing socioeconomic and behavioral characteristics among these groups. However, a substantial part of the disparity between blacks and Hispanics in comparison to whites could not be accounted for by such characteristics. We further found evidence to suggest that neighborhood environment plays a role in explaining BMI. Living in a poorer neighborhood was associated with slightly higher BMI among women, above and beyond individual socioeconomic status. Living in neighborhoods with a larger percentage of white residents was associated with lower BMI for both men and women. However, our evidence shows that, overall, individual characteristics mattered more than neighborhood characteristics in understanding obesity risk.

The efficacy of policy interventions designed to prevent obesity is ultimately conditional on our understanding of how "risk" characteristics operate. We found that the known correlates of obesity, including education, poverty, smoking, and walking, were strongly predictive of BMI among whites. Yet many of these same factors were not as salient for understanding BMI among blacks, Hispanics, or Asians. These findings provide further evidence that the processes and mechanisms that determine high body mass are complex. Moreover, many intervention studies have found no measurable effects from broad educational campaigns on behavioral change or weight status.

Taken together, the findings in this report underscore the importance of taking a multifaceted and tailored approach to obesity prevention. The racial and ethnic disparities in BMI and our limited ability to explain these inequalities may mean that public education efforts that aim to prevent and modify obesity should first strive to better understand the barriers to reducing obesity that may be unique to diverse groups. Doing so can help in the design of socially and culturally sensitive strategies that may improve the effectiveness of intervention efforts. For instance, Hispanics constitute a sizable and growing segment of the California population, and they represent 40 percent of the obese population in the state. These facts suggest that the need for engaging the Hispanic population in obesity prevention efforts cannot be understated.

Similarly, because both individual and neighborhood socioeconomic disadvantage measures appear to be related to higher BMI, focusing policy and public education efforts to help low-income people and low-income neighborhoods may constitute important groundwork for improving both individual and general well-being. Almost 39 percent of the obese population and about 31 percent of overweight Californians have incomes below 200 percent of the federal poverty level thresholds. About 25 percent of obese Californians and 21 percent of the overweight population in the state have less than a high school education. As noted in Chapter 4, 27 percent of obese individuals in California live in a poor neighborhood (defined as a neighborhood with at least a 20% poverty rate). Although obesity risk, as stated above, is considerable across the state, all these figures suggest that designing strategies that seek to understand barriers to obesity modification *and* that target obesity prevention in neighborhoods with high-risk populations may be central areas of emphasis for public health campaigns and interventions.

Several scholars of health policy and public health have questioned whether obesity prevention efforts can learn and draw lessons from the antismoking movement. Some have speculated that a snack tax policy should be modeled after the tobacco tax, which raised the price of the "unhealthy" product in question and used the tax revenues to fund public awareness and prevention. Indeed, there are some similarities between obesity prevention and tobacco control. For example, both smoking and obesity constitute serious public health risks and both must, in the end, be measured and driven by behavioral change. For both concerns, prevention is ultimately the most cost-effective and long-term strategy.

But important aspects make obesity prevention different from antismoking measures. Although people do not have to smoke, they do have to eat. And although the government could and did impose restrictions on the tobacco industry (e.g., selling and marketing to minors), policymakers may be hard pressed to impose similar types of restrictions on the food and beverage industries.

At the same time, there may be potential lessons to be learned for obesity prevention from tobacco control. Cigarette smoking rates have steadily decreased over the past few decades, most notably among younger cohorts. Some scholars have argued that a key component of smoking cessation trends included concerted partnerships among public health educators, government officials, physicians, and community organizations. Others have noted that measurable reductions in smoking rates required continued efforts among these partners over the course of many years. This example suggests that reducing obesity prevalence at the population level may require long-term commitments and collaboration among various individuals and institutions.

Appendix A

Notes on Data

Data Sources

Behavioral Risk Factor Surveillance System

Beginning in 1984, the CDC implemented the BRFSS, with 15 states, including California, participating. By 1990, all but six states were participating (nonparticipating states were Alaska, Arkansas, Kansas, Nevada, New Jersey, and Wyoming). By 1994, all states, including the U.S. territories, were participating.[1] Although health behavior data have been systemically collected over time in other national health studies (e.g., the National Health Interview Survey and the National Health and Nutrition Examination Survey), these other surveys often cannot produce reliable estimates for specific states.

The BRFSS was specifically designed to give states state-specific data on health risk behaviors annually and over time. The CDC has developed a standard "core" questionnaire component that each state administers to have comparable reports across states. Since its inception, the BRFSS has always included questions on self-reported weight and height. Data for each state are collected monthly by state health agencies, using computer-assisted random-digit dial (RDD) telephone interviewing (CATI). The Behavioral Surveillance Branch (BSB) of the CDC provides states with a sampling frame, and states use their own individual sampling methodology, approved by the BSB, to select households. CATI randomly selects one adult per household. After data collection, state reports are turned over to the CDC, which collectively pools the monthly data for all states and makes these data publicly

[1]More information about BRFSS is available through the CDC's website at http://www.cdc.gov/brfss/about.htm.

available by year. Response rates for the BRFSS are typically around 40 percent.

Our estimates from the BRFSS are based on annually released cross-sectional data of adults, and we relied on the balanced panel of states. For each year of data we examined, we chose to make some restrictions to the sample. Because of these restrictions, our estimates may be slightly different from those of other studies or reports using the BRFSS. First, we excluded women who were pregnant because their current weight status would not necessarily reflect their prepartum (depending on the stage of their pregnancy) or postpartum weight status. We excluded older teenagers (ages 18 and 19). For older teenagers, particularly males, final height has not been reached. We also dropped respondents who were age 70 or older. At these older ages, BMI can be confounded by the presence of other medical or chronic health conditions that develop with the aging process and misreporting can be more problematic. We also did not use cases where weight or height was unknown and BMI could not be calculated. Depending on the year, these criteria led us to exclude 4–6 percent of the potential analytic sample. Finally, we excluded cases where the calculated BMI was extremely low or extremely high, which led to the dropping of only a handful of the total cases in any given year.[2] Our BRFSS analytic sample for California differed from year to year, gradually increasing across the cross-sectional survey waves. The California sample for 1990, taking into account the restrictions described above, included 2,621 cases; in 1995, the sample size included 3,878 observations. By 2003, our California estimates were based on a sample size of about 4,300 adults.

California Health Interview Survey

The CHIS is a representative statewide telephone survey of adults, adolescents, and children in over 40,000 California households, conducted in 2003. The survey covers many health-related topics such

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[2]A self-reported BMI below 12 was considered to be a very low BMI and we could not be sure of its accuracy. For example, a 5’ 6” tall individual would have to weigh less than 75 pounds to have a BMI of less than 12. A self-reported BMI higher than 90 was considered to be a very high BMI.

as health status, health behaviors, and health insurance access and coverage.

The CHIS employed a two-stage, geographically stratified, RDD sampling design, using CATI similar to BRFSS. In the first stage, randomly generated California telephone numbers were divided into 41 strata (based on geographic areas: 33 counties and eight groups of counties with smaller populations). In the second stage, the CHIS randomly selected one adult per household to participate in the survey. The CHIS was conducted in six languages: English, Spanish, Chinese (Mandarin and Cantonese), Vietnamese, and Korean. The CHIS oversampled Vietnamese and Korean households, households in rural counties with small populations, and households in select cities in Alameda County (Oakland and Hayward) and Los Angeles County (all of the city of Los Angeles as well as the Antelope Valley Service Planning Area). An additional caveat (applicable to both the CHIS and BRFSS): Land-line telephone surveys may miss up to 6 percent of households, and this omission could be particularly problematic in areas with high cell phone use (Tucker et al., 2004; Blumberg, Luke, and Cynamon, 2004). The overall response rate for the CHIS in 2003 was about 34 percent.

Our analysis of the CHIS is based on a subsample of 33,285 adults, from the 41,437 respondents who were interviewed in 2003. We made a series of exclusions to the adult sample, based on a set of criteria similar to the restrictions we used for the BRFSS. In the CHIS, we dropped from our analytic sample women who were pregnant at the time of the interview (n = 436). We also excluded individuals whose information was collected via proxy interview, because they did not or could not answer questions for themselves. These individuals often included respondents over age 65, who did not have the ability to complete the interview, in which case a caregiver or individual close to the respondent completed the interview for that respondent. This led us to exclude an additional 171 cases. We also did not include older teenagers (ages 18 and 19) for reasons noted above (n = 950). In the CHIS, we also dropped respondents who were age 70 or older (n =5,919) because of the reasons described above for the BRFSS data.

We also excluded cases in which BMI was missing because of unreported or incomplete information for weight, height, or both.

Although the CHIS imputes BMI for respondents who do not report weight or height, we chose to exclude cases where BMI was imputed because of missing information. These restrictions led us to exclude an additional 981 cases.

We ran a logistic regression model predicting imputed BMI on a variety of sociodemographic indicators, to assess the extent to which excluding observations with missing BMI information may have affected our findings. The result of this exercise suggested that individuals who were of Hispanic origin, foreign-born, not in the labor force, and were poor (living below 100 percent of the federal poverty level) were significantly more likely to be missing information on weight and height. The magnitudes of the odds ratios suggest that Hispanics were about 32 percent more likely than whites to be missing BMI information. Foreign-born respondents in the 2003 CHIS were twice as likely as native-born individuals to have imputed values, and those living below 100 percent of the federal poverty threshold were also more than twice as likely (odds ratio = 2.2) as individuals living at or above 300 percent of the federal poverty level to be missing information on weight or height (or both). Also, people who were not in the labor force were about 60 percent more likely than those who were working at the time of the 2003 CHIS to have an imputed BMI. If these biases are the result of lack of knowledge regarding current weight or height status (e.g., because such individuals have not seen or had access to a health care provider), then it may be reasonable to assume that excluding these cases alters our conclusions. However, if these patterns stem from overweight or obese individuals censoring or not wanting to report their weight or height, then our findings will be underestimates of obesity/overweight prevalence and associations with BMI for these groups. In either case, we do not have enough information to say which way our sample may be skewed.

Finally, to have a consistent sample when examining the role of both individual and neighborhood characteristics, we also excluded cases where we could not link neighborhood information to the respondent using the respondent's zip code. Because relatively few observations were dropped for this reason, we believe that this restriction does not change the nature of our conclusions. More detail on merging neighborhood information with the CHIS (and observations excluded because of unmatchable cases) is available in Appendix B.

Because of these restrictions, estimates published in this report may not be comparable to other estimates using the CHIS. Also note that all estimates shown in both Chapters 3 and 4, drawing from the CHIS, were obtained from the same analytic sample of 33,285 individuals who met the criteria described above.

Estimating OLS Regressions

In Chapter 3, we presented results (coefficient estimates) obtained from simple OLS regression models predicting BMI for a variety of individual characteristics, using the 2003 CHIS analytic sample described above. These regressions were weighted using raked weights produced by the CHIS. The CHIS constructs person-level weights to account for the differential probability of selection of respondents. To be representative at the state level, weights are adjusted for nonresponse and raked to control totals provided by the 2003 California Department of Finance and the U.S. Census Bureau's 2000 Census of Population. (See CHIS (2005) for more information.)

Weighting estimates with the final weight computed by the CHIS provides estimates at the population level. To consider the complex sampling design used in the CHIS, we examined two different ways to calculate variances based on complex survey designs—Taylor series approximation and replication. We applied both of these methods to matching regression models using CHIS data. We found that the standard errors of regression estimates were largely identical. When we did find differences, they were of a small magnitude, less than 0.02, and often less than 0.01. Therefore, for simplicity, we decided to use the Taylor series approximation approach for calculating standard errors.

Table A.1

Sample Characteristics for Adults Ages 20–69, by Sex and Race/Ethnicity

	Sex		Race/Ethnicity			
	Men	Women	White	Black	Hispanic	Asian
Race/ethnicity						
White	48.3	48.2				
Black	5.7	6.7				
Hispanic	32.5	29.8				
Asian	11.2	12.7				
Sociodemographic						
Age (mean in years)	41.2	42.2	44.3	42.6	37.8	41.0
Sex						
Male			50.8	46.8	52.9	47.5
Female			49.2	53.2	47.1	52.5
Nativity status						
U.S.-born	64.5	67.2	91.1	93.2	37.1	19.1
Foreign-born	35.5	32.9	9.0	6.8	62.9	80.9
Years lived in the United States	17.4	17.6			16.9	16.0
≤ 5	4.3	4.2			7.1	12.1
6–10	5.4	5.2			10.0	13.2
11–15	6.3	5.7			12.6	13.5
16+	14.8	13.5			24.8	31.1
English ability						
Speaks English at home	86.0	86.6	97.3	97.8	71.7	72.1
Does not speak English at home	14.1	13.4	2.7	2.2	28.3	28.0
Marital status						
Married	58.7	56.2	60.3	39.4	54.9	65.2
Cohabiting	8.1	7.8	7.5	6.4	10.6	2.7
Separated/divorced/widowed	9.1	18.0	14.5	23.1	11.9	7.7
Never married	24.1	18.0	17.8	31.2	22.8	24.5
Education						
Less than high school	19.4	18.0	5.1	8.9	45.3	10.5
High school diploma/GED	21.8	21.9	21.1	27.1	23.8	15.6
Some college/vocational/ community college	24.5	28.0	29.9	36.9	20.0	20.5
College degree	20.2	20.3	25.2	16.9	7.8	35.4
Beyond college	14.2	12.0	18.8	10.1	3.2	18.2
% of federal poverty level						
< 100	12.4	15.6	5.0	15.6	27.8	13.5
100–200	16.7	18.5	9.9	18.4	30.1	15.1
200–300	13.3	13.4	12.1	15.4	14.7	13.4
300+	57.7	52.6	73.0	50.6	27.5	58.1

Table A.1 (continued)

	Sex		Race/Ethnicity			
	Men	Women	White	Black	Hispanic	Asian
Employment						
Employed	79.3	62.2	72.8	66.5	69.5	70.3
Unemployed	6.3	5.7	4.1	9.9	7.9	6.7
Not in labor force	14.4	32.16	23.1	23.6	22.6	23.0
Health care access and use						
Insurance status						
Currently insured	79.9	84.1	90.1	86.6	66.8	85.9
Uninsured	20.1	15.9	9.9	13.4	33.2	14.1
Regular source of health care						
Doctor/HMO	63.5	72.7	77.6	69.0	50.3	76.6
Clinic	15.1	15.3	9.5	18.2	25.2	9.6
Emergency room/no source of care	21.4	12.0	12.9	12.8	24.5	13.8
Behaviors						
Smoking						
Nonsmoker	51.3	66.9	52.3	57.9	65.7	72.0
Current smoker	26.9	18.9	28.6	20.8	18.3	13.2
Former smoker	21.8	14.2	19.1	21.4	16.0	14.8
Alcohol consumption						
No drinking	31.0	46.9	29.8	44.6	47.0	50.2
Drinks below recommended limit	63.3	48.3	62.9	51.7	49.3	48.1
Drinks above recommended limit	5.7	4.8	7.4	3.7	3.7	1.6
Walking behavior						
No walking	28.4	25.2	26.2	32.2	26.4	27.4
Low walking (< 60 min./week)	27.0	27.0	27.4	27.6	26.3	27.3
Moderate walking (60–150 (min./week)	22.2	23.8	23.0	21.5	22.9	23.5
Frequent walking (≥ 151 min./week)	22.4	24.0	23.4	18.7	24.3	21.9
Sample size	14,343	18,942	19,464	2,118	7,303	3,177

SOURCE: Author's calculations using the 2003 CHIS.

NOTE: Numbers shown are percentages, except for age (where we show the mean), and are weighted.

Table A.2

Description of Individual Characteristics

Variable	Description
Race/ethnicity	We adopt the California Department of Finance definition of race. Categories include: Hispanic, non-Hispanic Pacific Islander, non-Hispanic American Indian/Alaskan Native, non-Hispanic Asian, non-Hispanic African American, non-Hispanic white, non-Hispanic one other race, non-Hispanic two or more races
Age	A respondent's self-reported age
Sex	A respondent's self-reported sex
Nativity	Whether the respondent was born within or outside the United States
Years lived in the United States	For those respondents born in a foreign country, the length of time they have been living in the United States
English ability	We divided respondents into two categories: respondents who report speaking English only or English and another language at home; respondents who speak only another language at home
Education	Education is divided into five categories: less than high school; high school diploma/GED; some college, community college, or vocational school; college degree (bachelor's); beyond college
Marital status	We divide marital status into four categories: married, cohabiting, separated/divorced/widowed, and never married
Employment	Respondents are classified as: employed, unemployed, or not in the labor force
% of federal poverty level	Respondents are classified in terms of the relationship of their household income to the federal poverty level. The federal poverty level definition uses a set of income thresholds based on the size and composition of a family. For example, the 2003 poverty threshold for a family of four—consisting of two adults and two children—is $18,400.
Regular source of care	We use three levels of source of care: regular doctor/HMO, clinic or community hospital, emergency room/other place/no source of care
Insurance status	Respondents are classified as currently insured or currently uninsured
Smoking	We divided respondent into three smoking categories: currently smokes, former smoker, never regularly smoked

Table A.2 (continued)

Variable	Description
Alcohol consumption	Respondent were divided into three categories based on current U.S. Department of Agriculture guidelines for moderate drinking. Moderate drinking is defined as two drinks per day or less for men and one drink per day or less for women. Respondents' monthly drinking totals were calculated using questions about and amount of drinks per day and number of drinking days per week/month. Classifications are based on the average number of drinks per day: no drinking, moderate drinking, heavy drinking
Walking behavior	Walking categories are based on questions about the number of minutes and times per week/month a respondent walked for transportation and leisure. We calculated the number of minutes walked per week for each respondent and then divided the range of responses into quartiles: no walking for transportation or leisure, walked for 1–60 minutes per week, walked for 61–150 minutes per week, walked for 151 minutes or more per week

Appendix B

Notes on Neighborhood Data and Methodology

Data on Neighborhood Characteristics

For our analysis in Chapter 4, we created a unique dataset that merged characteristics from the zip code tabulation area level to information from CHIS respondents. The CHIS contains all respondents' zip code of residence. On average, there were about ten CHIS respondents per zip code tabulation area. To merge CHIS information with other sources of neighborhood data, we first used data collected in the 2000 Decennial Census. The Census reports data by ZCTA. The Census designed these ZCTA boundaries to be as consistent as possible with postal zip codes. Nevertheless, to use Census information, we needed to assign ZCTAs to each zip code in California. To match zip codes and ZCTAs, a map of ZCTA boundaries (from the 2000 Census cartographic boundary files) was overlaid with a map of zip code centroids (from Environmental Systems Research, Inc., ground conditions 00-01). Each zip code was allocated to the ZCTA in which the zip code centroid fell. In many instances, more than one zip code centroid fell within a ZCTA. In these instances the ZCTA was assigned to both/all zip codes.

Our second source of neighborhood information is the 2000–2001 Zip Code Business Patterns (ZBP) data, maintained by the Census Bureau. The ZBP has information on establishments, employment, and payroll by postal zip code. To obtain density measures for neighborhood establishments, we aggregated the number of certain types of establishments (identified by North American Industry Classification System codes) to the ZCTA level based on the matched zip code–ZCTA list described above. To get estimates per 1,000 residents in the ZCTA, we divided the average number of establishments in a ZCTA over 2000–2001 by the ZCTA Census population and multiplied the result by 1,000.

Last, we used information on homicide rates by neighborhood. We calculated homicide rates using cause of death information from the California Death Profiles, by Zip Code 2000–2002 collected by the Department of Health Services. The data describe the cause of death by victim's zip code of residence. The California Death Profiles reports information for only those zip codes where five or more residents die per year. Therefore, zip codes with missing information are assumed to have had no homicides in that particular year. To calculate homicide rates, we first summed the number of homicides in a zip code in 2000, 2001, and 2002. Next we aggregated zip codes to the ZCTA level. Finally, we divided the total number of homicides in a ZCTA by three times the Census ZCTA population and multiplied the result by 1,000 to create a three-year average homicide rate per 1,000 residents in a ZCTA. The homicide data we used reported a victim's zip code of residence rather than zip code of death. Therefore, our homicide rate should be interpreted as the rate of residents in a ZCTA who died as a result of homicide, rather than the rate of homicides committed in a ZCTA.

The neighborhood characteristics we constructed have some notable limitations. Our neighborhood constructs are at the ZCTA level, whereas the CHIS reports the zip code of a respondent's residence. We assigned zip codes to match ZCTAs in a systematic manner but some problems remain. Zip codes change over time, so if the 2003 CHIS respondents live in zip codes that changed between 2000 and 2003, the respondents may have missing or inaccurate ZCTA information. We assume that this error is small but have no way of checking. Furthermore, ZCTAs, particularly in rural areas, can be large. These areas may be less precise measures of "neighborhoods" than are more urban, smaller ZCTAs. Finally, to ensure a consistent sample, we were forced to exclude some CHIS respondents with missing neighborhood information. We dropped cases for two reasons: (1) In 104 cases, the respondent's zip code had no corresponding ZCTA or zip code business patterns data, and (2) in 14 cases, the respondent reported living in a zip code where the matched ZCTA had zero population.

Table B.1

Neighborhood Constructs

Construct	Source	Description
Racial/ethnic composition		
White	Census 2000 SF3	Percentage of total population that reports being white, non-Hispanic
Black	Census 2000 SF3	Percentage of total population that reports being black, non-Hispanic
Hispanic	Census 2000 SF3	Percentage of total population that reports being Hispanic
Immigrant concentration		
Foreign-born	Census 2000 SF3	Percentage of total population that reports being born outside the United States, Puerto Rico, or the U.S. island areas
Socioeconomic disadvantage		
In poverty	Census 2000 SF3	Percentage of people below the poverty threshold in 1999, out of the population in a ZCTA for whom poverty status is determined
On public assistance	Census 2000 SF3	Percentage of households on public assistance (general assistance and Temporary Assistance for Needy Families (TANF) in 1999)
Median family income	Census 2000 SF3	Median income of all families in 1999 dollars
Male unemployment rate	Census 2000 SF3	Percentage of male population age 16 and over that reports being in the labor force and not employed
Female unemployment rate	Census 2000 SF3	Percentage of female population age 16 and over that reports being in the labor force and not employed
Less than a high school diploma	Census 2000 SF3	Percentage of the population age 25 and over with less than a high school education/GED
Family structure		
Female-headed households with children under age 18	Census 2000 SF3	Percentage of all family households headed by women with their own children
Housing		
Vacant housing	Census 2000 SF3	Percentage of housing units that are vacant

Table B.1 (continued)

Construct	Source	Description
Disability		
Adults with physical or sensory disability	Census 2000 SF3	Percentage of adults ages 16–64 in the civilian noninstitutionalized population that report a sensory or physical disability
Commuting behavior		
Adults with commute times < 15 min.	Census 2000 SF3	Percentage of adults age 16 and over with commute times of less than 15 min.
Adults with commute times > 60 min.	Census 2000 SF3	Percentage of adults age 16 and over with commute times over 60 min.
Drive or ride motorcycle to work	Census 2000 SF3	Percentage of adults age 16 and over who drive or ride a motorcycle to work
Walk or bike to work	Census 2000 SF3	Percentage of adults age 16 and over who walk or bike to work
Neighborhood establishments/ resources		
Average number of grocery stores per 1,000 residents	Zip Code Business Patterns 2000–2001	Number of grocery stores (defined as NAICS category grocery stores, nonconvenience) divided by Census ZCTA population total multiplied by 1,000
Average number of convenience stores per 1,000 residents	Zip Code Business Patterns 2000–2001	Number of convenience stores (defined as NAICS category grocery stores, convenience and gas and convenience store/food mart) divided by Census ZCTA population total multiplied by 1,000
Average number of full-service restaurants per 1,00 residents	Zip Code Business Patterns 2000–2001	Number of full-service restaurants (defined as NAICS category full-service restaurants) divided by Census ZCTA population total multiplied by 1,000
Average number of limited-service restaurants per 1,000 residents	Zip Code Business Patterns 2000–2001	Number of limited-service restaurants (defined as NAICS category limited-service restaurants) divided by Census ZCTA population total multiplied by 1,000

Table B.1 (continued)

Construct	Source	Description
Average number of fitness or recreational centers per 1,000 residents	Zip Code Business Patterns 2000–2001	Number of fitness or recreational centers (defined as NAICS category arts and entertainment—fitness and recreational sports) divided by Census ZCTA population total multiplied by 1,000
Average number of liquor stores per 1,000 residents	Zip Code Business Patterns 2000–2001	Number of liquor stores (defined as NAICS category grocery stores, liquor) divided by Census ZCTA population total multiplied by 1,000
Ratio of grocery to convenient stores	Zip Code Business Patterns 2000–2001	Number of grocery stores divided by number of convenience stores (including gas stations)
Crime/safety		
Homicide rate (per 1,000)	California Death Profiles, by Zip Code 2000–2002	Three-year average of number of homicides divided by Census ZCTA population multiplied by 1,000

NOTES: All characteristics are calculated for a ZCTA. ZBP establishment information and homicide counts were averaged over two (ZBP) and three (California Death Profiles) years to create more stable estimates.

Methodology

Estimating Neighborhood Effects

To examine the role of neighborhood factors, we used multilevel models because these models allow us to examine the relative contributions of individual or personal characteristics *and* neighborhood characteristics to our outcome. We use both multilevel logistic regression (when predicting obesity as the outcome) and linear regression models (when predicting BMI as the outcome), but we present only the results from the linear regression models in this report. The results from the logistic regression models (when obese was the outcome) yielded similar results (these are available from the author). We employ

Table B.2

Neighborhood (Zip Code Tabulation Area) Characteristics for Adults Ages 20–69, by Race/Ethnicity

	White	Black	Hispanic	Asian
Racial/ethnic composition, %				
White	61.25	32.87	33.79	42.22
Black	4.05	19.81	6.71	5.25
Hispanic	21.30	32.81	47.09	25.57
Immigrant concentration, %				
Foreign-born	19.95	26.20	31.66	32.36
Socioeconomic disadvantage				
Median family income, $	64,009	47,953	46,738	63,399
Individuals in poverty, %	10.91	17.73	17.74	11.55
Households on public assistance, %	3.65	7.52	6.83	4.35
Male unemployment rate, %	5.91	8.77	8.33	5.78
Female unemployment rate, %	6.16	9.26	9.72	6.06
Less than a high school diploma, %	16.60	27.58	34.03	20.46
Family structure				
Female-headed households with children under age 18, %	8.99	13.91	11.57	8.88
Housing				
Vacant housing, %	5.41	4.95	4.68	3.43
Disability				
Physical or sensory disability, %	17.16	21.98	22.06	17.96
Commuting behavior				
Commute times < 15 min., %	27.26	21.84	24.11	22.21
Commute times > 60 min., %	10.11	11.38	10.47	9.90
Drive to work, %	87.32	85.48	86.63	86.21
Walk or bike to work, %	3.61	3.36	3.59	3.46
Neighborhood establishments/resources				
Average number of grocery stores per 1,000 residents	0.308	0.225	0.235	0.223
Average number of convenient stores per 1,000 residents	0.285	0.179	0.199	0.162
Average number of full-service restaurants per 1,000 residents	1.093	0.568	0.559	0.870
Average number of limited-service restaurants per 1,000 residents	0.809	0.593	0.590	0.713
Average number of fitness or recreational centers per 1,000 residents	0.121	0.057	0.049	0.079

Table B.2 (continued)

	White	Black	Hispanic	Asian
Average number of liquor stores per 1,000 residents	0.105	0.110	0.097	0.088
Ratio of grocery to convenient stores	1.458	1.610	1.556	1.820
Crime/safety				
Homicide rate (per 1,000)	0.045	0.137	0.087	0.049
Average population size	35,575	44,807	46,644	43,701

SOURCE: Author's calculations using the merged 2003 CHIS and neighborhood contextual data.

neighborhood fixed-effects and multilevel, random-effects, and discuss these approaches below.

In Chapter 4, we showed results from estimated models in which we controlled for neighborhoods or adjusted for living in the same neighborhood. This approach, known as fixed-effects, controls for all observed and unobserved characteristics of neighborhoods. These models allow us to look at differences or variations in BMI or obesity that exist within neighborhoods.

A disadvantage of the fixed-effects approach is that, because the models provide a perfect control for unobserved and observed neighborhood factors, we cannot tell from them what it is about neighborhoods that might matter for obesity nor can we tell which neighborhood characteristics help to explain racial/ethnic differences. Therefore, we also estimated multilevel, random-effects models in which we introduced specific measures of neighborhood context that might matter for obesity. Multilevel random-effects are widely used among social scientists (Kreft and De Leeuw, 1998) but have only recently been applied in attempts to understand obesity disparities (Boardman et al., 2005; Robert and Reither, 2004). This approach allowed us to estimate the associations of characteristics that are specific to individuals (e.g., education, poverty, smoking behavior, and health care use) and common to neighborhoods (e.g., racial/ethnic composition, neighborhood poverty, density of grocery stores, or homicide rates). The multilevel, random-effects models used in Chapter 4 can be represented by the following equation:

$$Y_{ij} = \alpha + \beta_k X_{ijk} + \beta_k Z_{jk} + \gamma_j + \varepsilon_{ij}$$

where
i = individual
j = neighborhood (ZCTA).

Here, Y is the BMI for each individual i in neighborhood j, X_{ijk} is the vector of independent variables for individual i in neighborhood j, and Z_{jk} is the vector of independent variables for neighborhood j. The random component of the neighborhood intercept is represented by γ_j and there is also a random component at the individual level, represented by ε_{ij}. Random-effects models rely on an assumption that the residuals are uncorrelated with the observed attributes.

Weighting in Multilevel Random-Effects Modeling

For most of the results reported in this study, we have weighted the estimates to account for the sample design and unequal probability of selection of respondents in the CHIS. However, we could not apply survey weights in the multilevel, random-effects models described above and discussed at the end of Chapter 4. We document these reasons here. The two main statistical packages we use (STATA 9.0 and SAS 9.0) cannot incorporate multilevel weights. Other software packages, such as MLWin, can account for various level weights, but we did not have such software available to us. It is incorrect to apply sample weights in a multilevel framework. To incorporate weights in these types of analyses, one should ideally construct or calculate appropriate multilevel weights (Asparouhov, 2004). STATA programmers recently created a macro to calculate and apply multilevel weights. The primary sampling unit (PSU) is required for these calculations. The CHIS does not have a PSU variable, which made running the macro problematic.

Because we could not run the multilevel, random-effects models weighted, we incorporated variables used in the sampling framework and design, including age, sex, English language use, and racial and ethnic background. Comparisons of unweighted estimates from nonmultilevel adjusted models to weighted estimates yielded similar results. We also ran regression models controlling for all neighborhood factors, running them with the survey weights and without weighting, and found largely comparable estimates.

Limitations

There are larger limitations to both of these approaches that should be noted. We know that individuals are not randomly assigned to live in various neighborhoods, and that where individuals or families choose to live is determined by a number of criteria, including resources of the neighborhood, school quality, crime, transportation, and racial homogeny or heterogeneity. The models that incorporate neighborhood characteristics cannot account for this selection. Because we can examine only cross-sectional relationships, we are not able to discuss pathways through which individuals come to live in different neighborhoods, or the long-term effects of community experience on obesity. Also, zip code tabulation areas may be too large an aggregation or approximation for a "neighborhood," particularly if the ZCTA covers a very large area.

Appendix C

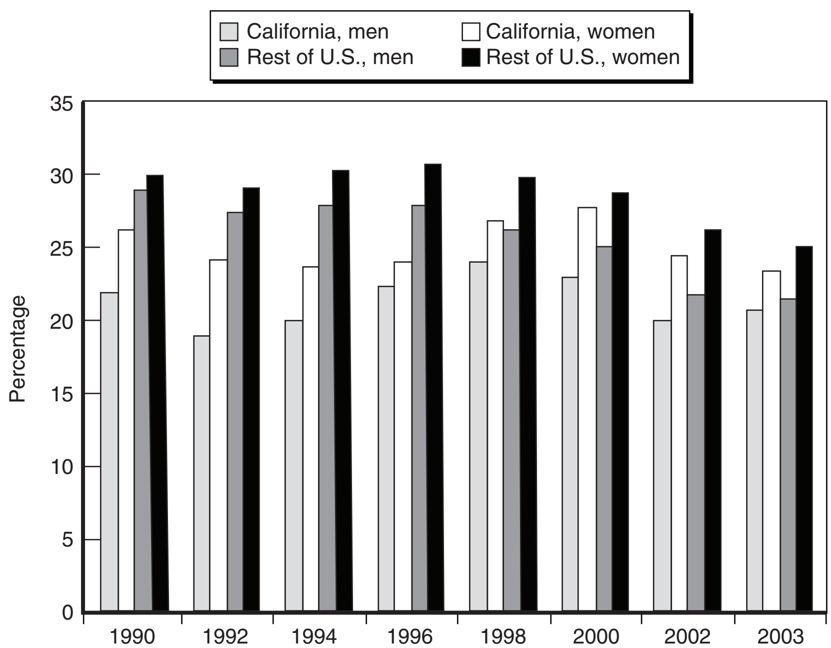
Trends in Physical Inactivity Levels and Nutritional Practices

As noted in Chapter 2, the two most important determinants of BMI are physical activity levels and caloric intake. In addition to their role on body weight regulation, physical activity and balanced diets have numerous other health benefits, including improved cardiovascular health and cancer prevention. In this appendix, we examine how physical inactivity (i.e., no reported leisure, exercise, or other physical activity) and fruit and vegetable consumption (i.e., whether respondents do not report eating at least five servings of fruits or vegetables a day) have also changed over time. These indicators are surely not comprehensive measures of caloric intake versus expenditure, but they do help illustrate patterns in obesity-related behaviors.

Our data are from the BRFSS, which, in even-numbered years, collects information on physical inactivity and dietary practices. The BRFSS physical inactivity question is worded, "The next few questions are about exercise, recreation, or physical activities other than your regular job duties. During the past month, did you participate in *any* physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise?" Respondents reporting no activity outside regular work duties are classified as physically inactive. The BRFSS physical inactivity question has changed slightly over the 1990-2003 period. The question above reflects the BRFSS questionnaire from 1990 to 2000. In 2001, the introduction was dropped (i.e., "The next few questions . . .") and respondents were asked about physical activities "other than your regular job" in the past *30 days*. In 2002 and 2003 respondents were asked about physical activities "other than your regular job" in the past *month*.

The dietary intake measure is based on six BRFSS questions asking about the frequency of consumption of fruit juices (e.g., orange, grapefruit, or tomato), fruit (not counting juice), green salad, potatoes (not including french fries, fried potatoes, or potato chips), carrots, and other vegetables (excluding green salad, potatoes, and carrots) in a respondent's diet. Dietary intake information was not systematically asked in all states until 1994. BRFSS questions regarding fruit and vegetable intake are identical from 1990 to 2003. Because questions regarding diet and exercise were not asked in every year of the BRFSS across all states, estimates are shown only for years in which this information was collected.

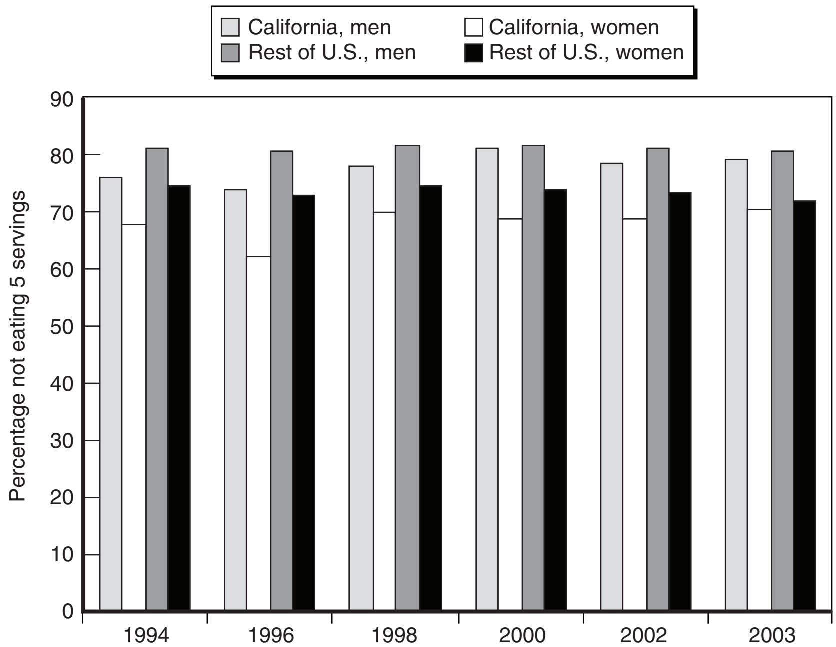
Turning to Figures C.1 and C.2, we see that physical inactivity levels and fruit and vegetable consumption seem to fluctuate slightly, but



SOURCE: Author's calculation using the 1990–2003 BRFSS.

NOTES: Estimates are shown for adults, ages 20–69, and are weighted. Estimates are age-standardized to the 2000 Census population.

Figure C.1—Trends in Physical Inactivity in California and the Rest of the United States, 1990–2003, by Sex



SOURCE: Author's calculation using the 1994–2003 BRFSS.
NOTES: Estimates are shown for adults, ages 20–69, and are weighted. Prevalence rates are age-standardized to the 2000 Census population.

Figure C.2—Trends in Daily Fruit and Vegetable Consumption in California and the Rest of the United States, 1994–2003, by Sex

overall, these behaviors appear to be largely stable when comparing the various survey years. We might have expected to see changes in sedentary activity or fruit and vegetable intake that would somehow parallel the BMI and obesity trends shown in Figures 2.1 and 2.2 in Chapter 2. Yet overall, these figures do not show a steady or consistent change in physical inactivity and nutritional intake, as measured by fruit and vegetable consumption.

There are other patterns to note from these figures. Men in general appear to have the lowest inactivity levels, and men in California have consistently lower rates of inactivity than men in the rest of the United States. In fact, both men and women in California have inactivity rates that are well below those of men and women in the rest of the United

States. In California, for both men and women, we see a slight upturn in physical inactivity rates in the mid- to late 1990s and then a decrease in inactivity rates in the early 2000s. Women and men in California are also less likely than those in the rest of the nation to report eating fewer than five servings of fruits and vegetables daily.

Appendix D

Regression Results

Table D.1

OLS Results Predicting BMI Among Men

	Model 1		Model 2		Model 3	
	Est.	SE	Est.	SE	Est.	SE
Race/ethnicity						
White						
Hispanic	1.52	0.14***	1.39	0.17***	1.35	0.17***
Black	1.21	0.24***	1.09	0.24***	1.03	0.24***
Asian	–1.60	0.20***	–1.16	0.22***	–1.21	0.22***
Native American/Alaskan Native	1.40	0.63*	1.05	0.66	0.98	0.66
Multiracial (2+)	–0.31	0.30	–0.50	0.30+	–0.46	0.29
Sociodemographics						
Age	0.26	0.03***	0.24	0.03***	0.23	0.03***
Age squared	–0.00	0.00***	–0.00	0.00***	–0.00	0.00***
Years lived in the United States						
U.S.-born			—	—	—	—
≤ 5			–0.69	0.38*	–0.60	0.38
6–10			–0.91	0.37**	–0.88	0.37*
11–15			–0.41	0.38	–0.43	0.38
16+			–0.55	0.19***	–0.54	0.19***
English ability						
Speaks English at home			—	—	—	—
Does not speak English at home			–0.30	0.28	–0.29	0.29
Marital status						
Married			—	—	—	—
Cohabiting			–0.31	0.23	–0.22	0.23
Separated/divorced/widowed			–0.50	0.20*	–0.38	0.20+
Never married			–0.96	0.16***	–0.83	0.17***
Education						
Less than high school			0.30	0.23	0.31	0.23
High school diploma/GED			—	—	—	—
Some college/vocational/ community college			0.22	0.16	0.21	0.16
College degree			–0.72	0.15***	–0.69	0.16***
Beyond college			–1.20	0.17***	–1.16	0.18***
Employment						
Employed			—	—	—	—
Unemployed			–0.01	0.23	0.08	0.23
Not in labor force			0.24	0.18	0.23	0.18
% of federal poverty level						
< 100			–0.05	0.26	0.00	0.25
100–200			0.05	0.19	0.09	0.20
200–300			0.23	0.18	0.23	0.18
300 +			—	—	—	—

Table D.1 (continued)

	Model 1		Model 2		Model 3	
	Est.	SE	Est.	SE	Est.	SE
Health care access/use						
Regular source of health care						
Doctor/HMO					—	—
Clinic					–0.11	0.19
Emergency room/no source of care					–0.57	0.18**
Insurance status						
Currently insured					—	—
Uninsured					0.27	0.21
Behaviors						
Smoking						
Nonsmoker					—	—
Current smoker					–0.27	0.17
Former smoker					0.35	0.13**
Alcohol consumption						
No drinking					—	—
Drinks below recommended limit					–0.17	0.13
Drinks above recommended limit					–0.44	0.26+
Walking behavior						
No walking					—	—
Low walking (< 60 min./week)					–0.35	0.16*
Moderate walking (60–150 min./week)					–0.63	0.17***
Frequent walking (≥ 151 min./week)					–0.80	0.17***
Constant	20.64	0.63***	22.03	0.70***	22.80	0.71***
R-squared	0.056		0.073		0.080	
Degrees of freedom	8		24		34	

SOURCE: Author's calculations using the 2003 CHIS.

NOTES: This table shows OLS estimates (and standard errors) predicting BMI. Model 1 controls for race/ethnicity, age, and age squared only. Model 2 adds controls for other sociodemographic characteristics (nativity, marital status, highest educational attainment, poverty level status, and employment). Model 3 adds controls for health care access and use (current insurance status and type of regular source of health care) and behaviors (smoking, drinking, and walking).

+Statistically significant at the 10 percent level.

*Statistically significant at the 5 percent level.

**Statistically significant at the 1 percent level.

***Statistically significant at the 0.1 percent level.

Table D.2
OLS Results Predicting BMI Among Women

	Model 1		Model 2		Model 3	
	Est.	SE	Est.	SE	Est.	SE
Race/ethnicity						
White						
Hispanic	2.78	0.16***	1.95	0.18***	1.73	0.18***
Black	3.06	0.25***	2.42	0.25***	2.11	0.26***
Asian	–2.60	0.16***	–2.11	0.18***	–2.47	0.19***
Native American/Alaskan Native	1.57	0.69*	0.62	0.67	0.46	0.68
Multiracial (2+)	1.22	0.38***	0.73	0.38+	0.71	0.38+
Sociodemographic						
Age	0.23	0.03***	0.31	0.03***	0.30	0.03***
Age squared	–0.002	0.00***	–0.00	0.00***	0.00	0.00***
Years lived in the United States						
U.S.-born			—	—	—	—
≤ 5			–1.48	0.31***	–1.44	0.31***
6–10			–0.99	0.38**	–1.12	0.38**
11–15			–0.79	0.33*	–0.85	0.33*
16 +			–0.53	0.20**	–0.53	0.20**
English ability						
Speaks English at home			—	—	—	—
Does not speak English at home			–0.01	0.29	–0.04	0.28
Marital status						
Married			—	—	—	—
Cohabiting			–0.13	0.23	0.10	0.23
Separated/divorced/widowed			0.12	0.17	0.24	0.17
Never married			0.24	0.19	0.43	0.19+
Education						
Less than high school			0.83	0.27**	0.77	0.26**
High school/GED			—	—	—	—
Some college/vocational/ community college			0.02	0.16	0.06	0.16
College degree			–1.34	0.16***	–1.19	0.16***
Beyond college			–1.31	0.17***	–1.16	0.18***
Employment						
Employed			—	—	—	—
Unemployed			0.32	0.30	0.45	0.31
Not in labor force			0.16	0.14	0.10	0.14
% of federal poverty level						
< 100			1.13	0.24***	0.91	0.25***
100–200			1.09	0.19***	0.87	0.19***
200–300			0.59	0.18***	0.45	0.18*
300+			—	—	—	—

Table D.2 (continued)

	Model 1		Model 2		Model 3	
	Est.	SE	Est.	SE	Est.	SE
Health care access/use						
Regular source of health care						
Doctor/HMO					—	—
Clinic					0.42	0.21*
Emergency room/no source of care					–0.47	0.22*
Insurance status						
Currently insured					—	—
Uninsured					–0.02	0.22
Behaviors						
Smoking						
Nonsmoker					—	—
Current smoker					–0.67	0.17***
Former smoker					0.42	0.15**
Alcohol consumption						
No drinking					—	—
Drinks below recommended limit					–1.17	0.12***
Drinks above recommended limit					–2.15	0.20***
Walking behavior						
No walking					—	—
Low walking (< 60 min./week)					–0.34	0.17*
Moderate walking (60–150 min./week)					–0.88	0.17***
Frequent walking (≥ 151 min./week)					–1.38	0.17
Constant	18.94	0.59***	17.76	0.69***	19.37	0.70***
R-squared	0.1055		0.131		0.151	
Degrees of freedom	8		24		34	

SOURCE: Author's calculations using the 2003 CHIS.

NOTES: This table shows OLS estimates (and standard errors) predicting BMI. Model 1 controls for race/ethnicity, age and age squared only. Model 2 adds controls for other sociodemographic characteristics (nativity, marital status, highest educational attainment, poverty level status, and employment). Model 3 adds controls for health care access and use (current insurance status, type of regular source of health care), and behaviors (smoking, drinking, and walking).

+Statistically significant at the 10 percent level.

*Statistically significant at the 5 percent level.

**Statistically significant at the 1 percent level.

***Statistically significant at the 0.1 percent level.

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