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UNIVERSITY OF MIAMI

THE EFFECT OF ECONOMIC AND SOCIAL CONDITIONS ON THE USE OF CLINICAL PREVENTIVE SERVICES

By

Bisma Ali Sayed

A DISSERTATION

Submitted to the Faculty
of the University of Miami
in partial fulfillment of the requirements for
the degree of Doctor of Philosophy

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THE EFFECT OF ECONOMIC AND SOCIAL CONDITIONS ON THE USE OF CLINICAL PREVENTIVE SERVICES

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This study examines the relationship between economic conditions and individuals' use of clinical preventive (CP) services. CP services form the cornerstone of the national healthcare agenda, and are key in the fight to reduce morbidity and mortality in the United States. Despite this, low utilization rates remain concerning, with recent statistics indicating that rates of CP service use fall well below the targets outlined in Healthy People 2020. In the present study, I focus on individuals' use of three CP services, influenza vaccinations, blood cholesterol screening, and endoscopic colorectal cancer screening. Broadly, I examine the effect of state-level unemployment and income inequality on individuals' use of these services. I also explore underlying social mechanisms that may shape these behaviors. Specifically, I examine how social contextual factors, state-level social capital and health-related resources, affect individuals' use of CP services net of individual-level characteristics.

The data from this study is derived from a variety of sources. Contextual-level data is obtained from the Bureau of Labor Statistics, Mark W. Frank's Income Inequality Measures, the General Social Survey, the Association of American Medical Colleges, the Current Population Survey, and the Centers for Disease Control and Prevention.

Individual-level data is obtained from the 2010 and 2011 Behavioral Risk Factor Surveillance System. I use multilevel models to examine how contextual factors shape individuals' use of CP services. I also include a range of individual-level variables to capture the socio-demographic, economic, lifestyle, and health-related characteristics that shape individuals' use of CP services.

Findings suggest that the relationships between state-level economic and social factors, and CP services differ by the specific CP service examined. Specifically, results suggest the state-level unemployment and income-inequality are significantly and negatively associated with individuals' use of influenza vaccinations, after taking into account individual-level characteristics. Findings also reveal that state-level unemployment is significantly and positively associated with individuals' use of blood cholesterol screening and endoscopic colorectal cancer screening. Additionally, results indicate that some social conditions also shape individuals' use of CP services. Specifically, confidence in the media is a salient predictor of individuals' use of influenza vaccinations, blood cholesterol screening, and endoscopic colorectal cancer screening. Social trust is an important predictor of individuals' use of endoscopic colorectal cancer screening. Health-related resources, specifically primary care physician supply and participation in the Colorectal Cancer Control Program, are also salient predictors of individuals' use of endoscopic colorectal cancer screening.

Findings also point to significant relationships between individual-level variables and use of CP services. Broadly, across all CP services examined, socio-demographic and economic (e.g. age, gender, income, employment status) and health-related factors, particularly health insurance and health status, are salient in predicting individuals' use of CP services.

Most of the existing research on CP service use focuses on individual-level determinants of use, and broader economic and social conditions are frequently ignored. Findings from the current study suggest that contextual economic and social factors impact individuals' decisions to use CP services net of individual-level factors. Thus, efforts should be made to address the contextual economic and social features of the environment that shape individuals' use of CP services.

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"And He found you lost and guided you."
93:7, Al-Quran

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"So, verily, with every hardship there is ease."
94:5-6, Al-Quran

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Chapter One: Introduction

According to the U.S. Preventive Services Task Force (USPSTF, 2010), clinical preventive (CP) services are medical procedures designed to prevent disease altogether and/or detect disease early, often before costly medical interventions are necessary (USPSTF, 2010). These include, for example, health care screenings for breast cancer, cardiovascular disease, and colorectal cancer, as well as vaccinations for influenza, pneumonia, varicella, and HPV (USPSTF, 2010). A plethora of research documents the positive health benefits of obtaining recommended and routine CP services (USPSTF, 2010; Department of Health and Human Resources, 2013). Use of recommended CP services is associated with lower incidence of infectious diseases (e.g. influenza) and better prognosis for many diseases (e.g. heart disease and heart attacks) if illness is detected (USPSTF, 2010; DHHS, 2013). Moreover, evidence also indicates that timely use of recommended CP services reduces the overall cost of healthcare because illness is often diagnosed in earlier stages when more expensive treatment can be avoided (USPSTF, 2010; DHHS, 2013). The USPTSF (2010) provides clinical recommendations on the use of CP services based on age, gender, and risk profiles. According to Healthy People 2020, CP services form the cornerstone of the United States' national healthcare agenda (DHHS, 2013).

Despite the benefits of obtaining CP services, underutilization is a critical problem. Recent statistics show that the majority of CP services remain underused, particularly for individuals who lack health insurance (Centers for Disease Control and Prevention, 2006; DHHS, 2013). For example, although blood cholesterol screening rates have gone up in the last ten years, they still remain below targets outlined in Healthy People 2020. Similarly, according to the National Health Interview Survey (NHIS), only a little over a quarter of adults between 18 to 49 years of age report receiving the influenza vaccination in the past year (CDC, 2014b; Williams et al., 2014). While this is higher among older individuals ages 50-64 (42.7%) and adults 65 years and over (66.5%), rates nonetheless remain concerning (CDC, 2014b). The situation is even more serious for some types of health screenings such as colorectal cancer screening, where rates of endoscopic exams (e.g. colonoscopy and sigmoidoscopy) are well below targets outlined in Healthy People 2020 (Boyles, 2012).

Many factors are implicated in individuals' low use of CP services, including socio-demographic, economic, health, lifestyle, and behavioral characteristics (Coe, Gatewood, Moczygemba, and Beckner, 2012; Eckersley, Dixon, & Douglas, 2001; Carrieri and Bilger, 2009; Grispen et al., 2011). Although many studies examine the individual-level correlates of CP service use, few studies examine the relationship between contextual factors such as state-level unemployment, income inequality, social capital, and health related resources, and individuals' use of CP services. Among studies that do examine contextual factors, most employ ecological study designs. These studies assess how economic and social features of the environment affect rates of CP service use across geographical units. Thus, very little is known about how contextual factors affect individuals' decisions to use CP services. Some studies (cf. Ruhm, 2000; Tefft & Kageleiry, 2013) that examine individuals' use of CP services rely on pooled cross-sectional data over time. While these studies are appropriate and rigorous because they predict individual-level outcomes and control for time and state-level differences, findings are mixed and some contextual factors are underexplored, so further research is necessary.

The current study builds on the existing literature by examining the relationship between state-level economic conditions and individuals' use of CP services, specifically focusing on three CP services that are recommended for men and women, influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screenings. I also explore the underlying causal mechanisms that have been highlighted in the literature, the role of state-level social capital and neo-material resources in shaping individuals' use of CP services. Importantly, I examine the links between economic conditions and CP service use after taking into account individual-level resources such as income and health insurance.

This dissertation is organized in eight chapters. Each chapter focuses on a particular aspect of the project.

Chapter Two: In this chapter, I begin by examining the three specific CP services chosen for the current study. I highlight the current recommendations and explore the accessibility, side effects, safety, and effectiveness associated with each CP service. I then shift gears to outline the existing theories that can be used to examine how contextual- and individual-level factors shape individuals' use of CP services.

Chapter Three: In this chapter, I explore the existing literature on economic conditions and health, paying specific attention to studies that examines links between economic conditions, health behaviors, and health services utilization. Wherever possible, I review studies that examine how economic conditions shape individuals' use of CP services.

Chapter Four: In this chapter, I explore the intervening social mechanisms that are highlighted in the literature, social capital and neo-material resources. I examine the existing literature on social capital and health, paying specific attention to studies that explore the relationships between social capital and health behaviors, health services utilization, and CP service use. To examine the relationships between neo-material resources and individuals' use of CP services, I limit the study to health related resources. Specifically, I examine the relationship between primary care physician supply and health services use, and review these studies in detail.

Chapter Five: In this chapter, I outline the conceptual model for the current study. I also outline the research questions that guide the current study, as well as the hypotheses that have been developed based on the existing literature.

Chapter Six: In this chapter, I explain the data and methods used for the current study. There are multiple sources of data for the current study. Contextual level data is obtained and/or derived from the Bureau of Labor Statistics, Mark Frank's data on income inequality, the General Social Survey, the Current Population Survey, the 2011 State Physician Workforce Data Book, and the Centers for Disease Control and Prevention. Individual-level data is obtained from the 2010 and the 2011 Behavioral Risk Factor Surveillance System. I also provide information on the main analytical method employed, multilevel modeling, and the approach taken to build models and examine the main hypotheses.

Chapter Seven: In this chapter, I explain the results for each CP service outcome examined. Specifically, for blood cholesterol screening, colorectal cancer screening, and influenza vaccination, I outline the results from the multilevel models and the stratified analysis.

Chapter Eight: In the final chapter, I briefly review the main findings of the current study, and discuss the possible mechanisms that may explain the relationships between state-level economic conditions, social conditions, and individuals' use of CP services. I also outline the strengths and the limitations of the current study. I conclude by exploring the policy implications.

Chapter Two: Clinical Preventive Services and Theoretical Frameworks

In this chapter, I begin by reviewing the three CP services that are the focus of the current study, influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screening. I review the current clinical recommendations, and provide a brief background on the accessibility, effectiveness, and safety issues surrounding each of these services. These factors are important to consider because they may affect how economic and social conditions shape use of CP services. I then shift gears to outline the key theoretical frameworks that are available for understanding health care utilization. These theories will be used to guide the study. Although these theoretical frameworks have not been designed explicitly for predicting individuals' use of CP services, they can and have been extended to do so.

Clinical Preventive Services

CP services are key in the fight to improve morbidity and mortality. According to the USPSTF (2010), there are four types of CP services, behavioral counseling services, screening tests for asymptomatic disease, chemoprophylaxis, and immunizations. This study examines two types of CP services, immunizations and screening tests. Specifically, I examine the economic and social determinants of influenza vaccinations, blood cholesterol screening, and colorectal cancer screening use. These CP services are chosen because they represent a range of CP services in terms of accessibility, effectiveness, risk, and safety.

Influenza Vaccinations

The Centers for Disease Control and Prevention (CDC) estimates that in the past three decades, the number of deaths due to influenza has ranged from a low of 3,000 to a high of 49,000 (CDC, 2014a; CDC, 2014b). Annual influenza vaccinations or nasal sprays are the major public health strategies available to prevent the flu (CDC, 2014b). Influenza vaccinations are recommended for all persons older than 6 months, with few exceptions[1]. Individuals can choose to obtain the flu vaccine, which requires an injection of dead flu viruses, or the flu nasal spray, which requires inhaling weakened live viruses (CDC, 2014a; CDC, 2014b). Because the influenza virus can change via antigenic drift and antigenic shift mechanisms, new flu vaccines must be developed for every flu season and individuals must be vaccinated every year (CDC, 2014a; CDC, 2014b).

The flu vaccine (and nasal spray) can be received in various clinical settings, including physicians' offices and retail pharmacies (CDC, 2014b). In many settings, appointments are not necessary and it takes very little time to receive the vaccine. There are no immediate adverse effects of the vaccine, beyond tenderness at the injection site (if an injection is chosen), so individuals can return to their daily routines immediately (CDC, 2014b). The average cost of an influenza vaccination is approximately thirty dollars in retail settings without insurance (CDC, 2014b). With insurance, individuals may incur a small copay. In some low-income communities, free influenza vaccinations are available (Jacobson, 2013).

There are numerous concerns surrounding the safety and efficacy of influenza vaccinations (CDC, 2014b). First, there are many reported side effects, though most are

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[1] Individuals with egg allergies, Guillain-Barre Syndrome (GBS), and those who are seriously ill should not obtain the annual influenza vaccination (CDC, 2014b).

relatively mild. Commonly reported side effects include soreness at the injection site, low-grade fever, and aches and pains (CDC, 2014b). Individuals who opt to obtain the nasal spray may have to contend with runny nose, wheezing, headaches, vomiting, muscle aches, and fever (CDC, 2014b). Although the possibility of serious side effects is present (e.g. severe allergic reaction, Guillain-Barre Syndrome), the vast majority of individuals do not experience any serious adverse effects due to vaccination (CDC, 2014a). Second, there is substantial concern surrounding the efficacy of the flu vaccine. In fact, there is much speculation and some research suggesting that the influenza vaccine may in fact be ineffective for most of the population (Rabin, 2012; Osterholm et al., 2012). There is also public concern that the vaccine is unsafe (Clachar, 2008; Parker-Pope, 2009). Indeed, there are numerous websites outlining the risks associated with the vaccine, with some websites advising the public to avoid getting the vaccine altogether and going as far as saying that the vaccine may actually cause illness or other adverse health conditions (CDC, 2014a; Clachar, 2008; Parker-Pope, 2009).

Blood Cholesterol Screening

Blood cholesterol screening is the major public health strategy used to identify individuals at risk for coronary heart disease, stroke, and atherosclerosis (CDC, 2014c). High blood cholesterol is a major risk factor for heart disease, which is widely known to be the leading cause of death among men and women in the United States (CDC, 2014c). Blood cholesterol screening allows health care professionals to identify patients at risk of developing heart disease or a heart attack. To date, there are no universally accepted recommendations for blood cholesterol screening. The USPSTF (2010) recommends blood cholesterol screening for men age 35 and older, and women age 45 and older if they are at increased risk for heart disease. There is, however, a push to recommend screening at younger ages. In fact, some national health agencies such as the National Cholesterol Education Program (NCEP) and the American Heart Association (AHA) recommend blood cholesterol screening every five years for adults ages 20 and over (AHA, 2014; NCEP, 2004). Screening at more frequent intervals is recommended if initial baseline tests are abnormal and if individuals report a family history of high cholesterol or heart disease (AHA, 2014). Frequent screenings are also recommended if individuals smoke, and/or have been diagnosed with diabetes or high blood pressure (Nagourney, 2007; Parker-Pope, 2008).

Blood cholesterol screening is a relatively noninvasive medical procedure. It is conducted by withdrawing a sample of blood that is tested for low-density lipoproteins, high-density lipoproteins, total cholesterol, and triglycerides (AHA, 2014; NCEP, 2004). Individuals are typically asked to fast for twelve hours prior to having the test; for this reason, the test is typically conducted in the morning (AHA, 2014; NCEP, 2004). Blood cholesterol screenings can be done at a variety of locations, but they are more often requested by primary care physicians as part of standard checkups or stand alone tests. Since mid-2011, some retail clinics offer blood cholesterol screenings in select locations, as well (Walgreens, 2011). There are no adverse health effects of obtaining blood cholesterol screenings so individuals can resume their daily routines immediately after the appointment (AHA, 2014). In retail clinics, the cost of blood cholesterol screening ranges from $25 to $35 and the service is typically covered for those with health insurance. At physicians’ offices, the cost of blood cholesterol screening tests may be higher because physicians often bundle blood cholesterol screening with other tests (Bishop, Federman, & Ross, 2010).

Blood cholesterol screening is a well-accepted strategy to identify high cholesterol, with no side effects, beyond tenderness at the site where blood is drawn. Thus, these tests are considered to be safe and accurate, with little risk involved. Despite this, it is important to note that blood cholesterol screenings requires patients to fast for at least 12 hours, a factor that may serve to dissuade individuals from obtaining the test. Interestingly, research suggests that individuals are both aware of blood cholesterol tests and understand their importance (Rubin, 2000; Goldman et al., 2006). In fact, Rubin (2000) notes that most barriers to blood cholesterol screening do not revolve around patient safety or efficacy concerns, but arise from within a healthcare system that often overlooks preventive care in favor of acute treatment.

Colorectal Cancer Screening

Colorectal cancer is cancer that begins in the colon or rectum. It is the second leading cause of cancer-related deaths (U.S. Cancer Statistics Working Group, 2013). Colorectal cancer screening is instrumental in combating rising rates of colorectal cancer (National Center for Health Statistics, 2012; USPSTF, 2014b). Screening consists of a multistep approach that includes the use of fecal occult blood tests (FOBT) and endoscopic procedures, namely, colonoscopies and sigmoidoscopies (USPSTF, 2014b). There are also alternative tests that are sometimes used such as virtual colonoscopy and double-contrast barium enema (Colon Cancer Alliance, 2014; National Cancer Institute, 2013). The USPSTF (2014b) recommends that all adults between the ages of 50 and 75 years be screened for colorectal cancer. FOBT is recommended yearly for this age group.

Sigmoidoscopy is recommended every five years if FOBT is done regularly. A colonoscopy is recommended every ten years. In the current study, I focus on the endoscopic screening exams, colonoscopy and sigmoidoscopy.

Sigmoidoscopy and colonoscopy are invasive medical examinations of the colon. The major difference between a colonoscopy and a sigmoidoscopy is that the latter is able to provide images only of the left side of the colon while the former examines the entire colon (CCA, 2014). Physicians perform a sigmoidoscopy by inserting a sigmoidoscope into the rectum (CCA, 2014). Although the test itself lasts 10 to 20 minutes, individuals must prepare for the test by using enemas and/or laxatives to cleanse the bowel (CCA, 2014). During the procedure, individuals may experience cramping, gas, pain, and discomfort (CCA, 2014). If abnormalities are detected during the procedure, a biopsy is done and a colonoscopy is also performed (CCA, 2014). Although sigmoidoscopies are done in about 20 minutes and sedation is not required, individuals may request medication. If sedatives are not used, most individuals can resume their daily routine the same day after obtaining a sigmoidoscopy (CCA, 2014).

Colonoscopies are considered to be the gold standard in colorectal cancer screening (CCA, 2014). Before undergoing a colonoscopy (and a sigmoidoscopy), individuals must cleanse their bowel by using a combination of diet, laxatives or enemas (CCA, 2014). The colonoscopy is performed by inserting a colonoscope, a four-foot long, flexible tube, into the rectum (CCA, 2014). Both the sigmodoscope and the colonoscope are equipped with a camera and a source of light to provide images of the colon (CCA, 2014). Individuals undergoing colonoscopies are usually offered sedatives or other anxiety reducing medication (CCA, 2014). Individuals may be placed on IV fluid, heart rhythm and blood pressure monitoring devices (CCA, 2014). If abnormalities are detected, a biopsy is conducted. If polyps are present, they are usually removed during the procedure (CCA, 2014). Individuals cannot resume their daily routines immediately after undergoing a colonoscopy (CCA, 2014).

Endoscopic exams to detect colorectal cancer are expensive medical procedures typically performed on an outpatient basis by primary care physicians or gastroenterologists (CCA, 2014). The cost of a sigmoidoscopy ranges from an average of $500 to $750 for those without insurance (CCA, 2014). Colonoscopies are significantly more expensive, with average costs ranging from $800 to $1600 (CCA, 2014). Although these exams are covered by insurance, even those who are insured may still need to pay copayments or deductibles (CCA, 2014).

Colonoscopies and sigmoidoscopies are invasive medical procedures (CCA, 2014). Although both procedures are considered to be generally safe, there are instances of rare complications such as perforation of the colon and bleeding; however, this occurs in less than 1% of cases (CCA, 2014). If sedatives are used, irritation at the injection site may also be present (CCA, 2014). Moreover, use of sedatives prevents individuals from resuming their daily routines immediately post procedure (CCA, 2014). If polyps are detected and removed, individuals may need to modify their diet for a period of time (CCA, 2014). Given the invasive nature of endoscopic tests, it is not surprising that limited awareness of clinical recommendations, anxiety about the procedures, fear, and embarrassment are major barriers to use (Austin et al., 2009; Consedine et al., 2011; Croyle, 1995).

Overall, these CP services are distinct in terms of accessibility, effectiveness, and safety and risk perceptions. Despite these concerns, however, evidence suggests that recommended use of these services is advantageous to health. However, underuse remains a serious concern, and there is reason to suspect that broader economic and social conditions may affect individuals' use of these services. I use two major theoretical frameworks, Grossman's (1972) human capital model of the demand for health and Andersen's behavioral health model, to better understand the multiple and multilevel determinants of CP service use.

Key Theoretical Frameworks

Recent research recognizes the role of multiple factors, both individual and contextual, in shaping individuals' use of healthcare services. Grossman's (1972; 1999) human capital model of the demand for health and Andersen's behavioral health model provide important insight into the factors that shape individuals' use of health services. Grossman's (1972) human capital model is based on human capital theory. Human capital theory is grounded in an economic perspective, whereby social and personal attributes, including health, give rise to economic production (Grossman, 1999). Andersen's (1995) behavioral health model, on the other hand, approaches health from a sociological perspective, taking into account both individual and structural determinants of health services use. I also incorporate some aspects of Rosenstock's (1974) health belief model, which provides insight into how individuals' health related beliefs impact their use of CP services. While there is some overlap between these models, they are also complementary and are appropriate for understanding individuals' use of CP services.

Grossman's Human Capital Model of the Demand for Health

Grossman's (1972) model of healthcare demand provides an important starting point for understanding how individuals view health and make decisions regarding the use of health services. According to Grossman (1972), investments in health are viewed as investments in human capital. Similar to other types of human capital (e.g. education and income), health is also a form of capital, but it serves both consumption and investment functions (Grossman, 1972). Each individual possesses an initial baseline stock of health that declines with age, with more rapid declines occurring in older age (Grossman, 1972). Individuals can invest in their health through health producing activities (e.g. medical care utilization, proper diet and nutrition, physical activity, and use of CP services).

From this perspective, the use of CP services represents individuals' decisions to invest in their health (Grossman, 1972). Investment, however, varies by a range of human capital characteristics, including age, education, and income (Grossman, 1972), and the direction of the relationships are not always straightforward. For example, older individuals are more likely to have a higher demand for some types of health services due to declining health stock. It is also possible, however, that past a certain age, older individuals may choose to forego health investments because the cost is too great relative to the perceived benefits. The model also outlines the relationship between income and investment in health, noting that individuals with high incomes may place a greater value on their health and thus may be more likely to use health-producing services (Grossman, 1972). However, it is also plausible, under this framework, that individuals with greater incomes may forego health investments that are considered to be too time intensive

(Grossman, 1972; Fuchs, 1982). According to Grossman (1972), the role of education is relatively straightforward. Individuals with higher education are more likely to engage in health-producing activities primarily because they are aware of the positive consequences of such investments.

While Grossman's (1972) human capital model for health care demand provides important information on the human capital determinants of health care use and has been widely used in the literature, there are a number of criticisms.

First, the original model does not differentiate between necessary medical care and preventive medical care, even though there is substantial difference between the two (Dardanoni & Wagstaff, 1990). Labeit and colleagues (2013, p.6) discuss this issue, noting that, "acute care represents especially the consumption aspect of health whereas preventive care (i.e. screening services) represents the investment aspect." This distinction has important implications. Because the use of preventive services is an investment in the future, it is likely that discounting serves as a major barrier in individuals' decisions to use CP services (Bradford, 2009). Discounting refers to individuals' tendency to assign lower weights to benefits and costs that occur in the future and greater weights to immediate benefits and costs (Bradford, 2009; Grossman, 2000). Existing research suggests that individuals discount many aspects of their life, including health (Bradford, 2009; Grossman, 2000). Discounting may be especially important in the use of preventive service because the benefits accrue in the future while the costs are immediate. Thus, an individuals' use of preventive services, unlike their use of acute healthcare services, suggests the extent to which they value the future over the present (Bradford, 2009). While this was not addressed in the initial model, subsequent research has extended the model to include notions of discounting (Bradford, 2009; Grossman, 2000).

Another major criticism of Grossman's model is its limited attention to environmental or structural factors (Leibowitz, 2004). Some researchers propose a broader view of health production that includes contextual inputs (Leibowitz, 2004). Thus, the model has been extended to include family, organizational, and contextual characteristics (Leibowitz, 2004). Still another concern is that the model does not explicitly take into account the effect of insurance (Kenkel, 1994). In his work on preventive care use, Kenkel (1994) finds that health insurance plays an important role in preventive care, and argues that any research on health utilization must take into consideration the role of health insurance.

Despite these concerns, Grossman's (1972) model provides important insights into the role of human capital factors in the use of care. Many studies use Grossman's model of health to guide research on healthcare use as well as health behaviors. The model has been used, for example, to better understand and predict emergency room use, hospitalizations, and mental health services use (Haas-Wilson, Cheadle, and Scheffler, 2001). The model has also been used to explain modifiable health related behaviors such as smoking, alcohol use, and physical activity among others (Muurinen & Le Grant, 1985; Grossman, 2000; Grossman, Chaloupka, & Sirtalan, 1995). Importantly, the model has been employed to better understand individuals' use of preventive services. Labeit, Peinemann, and Kedir (2013), for example, use a modified version of Grossman's (1972) original model that takes into account multiple multilevel factors (e.g. individual, family and attitudinal characteristics) to examine use of cervical cancer screening in the United

Kingdom. Studies also use the model to examine how individuals' risky behaviors affect their use of CP services such as breast cancer screening and influenza vaccination (Ettner, French, and Popovici, 2010; Wubker, 2012).

To address some of the limitations of Grossman's (1972) model, I also employ Andersen's (1995) behavioral model to guide the study. This model provides the flexibility to consider the individual- and contextual-level factors that shape health services use.

Andersen's Behavioral Health Model

The Andersen behavioral model of health services utilization (Andersen, 1995; Andersen & Neuman, 1973) is perhaps the most widely used health services utilization model in sociology and public health. Since the initial development of the model in 1968, there have been several revisions and additions to the model to account for greater knowledge about health services use and the changing healthcare infrastructure in the United States (Andersen, 1995). While the purpose of the original model was to predict primary health services utilization (Andersen, 1995), subsequent revisions have extended the model to examine a range of health related behaviors, making it ideal to examine individuals' use of CP services.

The original model identified three major components of healthcare use: predisposing characteristics, enabling characteristics, and need (Andersen, 1995). Later additions highlight the role of broader social, political, and organizational determinants of healthcare use (Andersen, 1995). These include, for example, the broader environment such as health care systems and other external factors, as well as personal health practices, attitudes towards health care, and consumer satisfaction with the health care system (Andersen, 1995). Thus, the model allows for a comprehensive examination of health services use from a systematic perspective that takes into account the broader social conditions within which services are accessed as well as the individual-level human capital characteristics that shape healthcare use.

The most recent revision of Andersen's (1995) model begins by identifying features of the external environment that shape health, health behaviors, and healthcare use. Within this framework, the external environment includes characteristics of the health care system and other social factors that shape individuals' health behaviors (Andersen, 1995). These can include, for example, physical, political, and economic factors within which the healthcare system operates (Andersen, 1995). Indeed, the external environment component explicitly recognizes the role of the broader environment, such as economic conditions, that shape individuals' health, health behaviors, and healthcare use. Thus, contextual-level income inequality and unemployment can be included as features of the social environment that shape individuals' use of CP services.

Predisposing characteristics consist of socio-demographic and social structural factors at the individual-level (Andersen, 1995). Specifically, predisposing factors include individual-level social status measures such as education and occupation. Predisposing factors also include individuals' degree of self-efficacy, health beliefs, and attitudes toward health care. Anderson (1995) notes that social networks can also be included as predisposing factors.

Enabling characteristics include both individual- and community-level resources that shape individuals' use of health care services (Andersen, 1995). For example, on an individual-level, income and health insurance are considered salient resources that enable individuals to access the health care system. On a contextual-level, enabling factors also include social networks, social capital, social cohesion, and other community or organizational characteristics that affect healthcare use (Andersen, 1995). Contextual-level neo-material resources that facilitate access to healthcare services (e.g. availability of primary care physicians within a given area) can also be included as enabling features of the environment.

Need factors consider individuals' evaluation of their own health as well as their beliefs about health risks. Specifically, the need for health care can be evaluated with both subjective and clinical assessments (Andersen, 1995). Subjective health assessments refer to individuals' perception of their own health. Clinical health assessments are based on professional evaluations. Routine use of health care services, including CP services, and adoption of healthy behaviors are based primarily on subjective health assessments, while use of necessary medical treatments are largely due to clinical assessments of health (Andersen, 1995; Glanz, Rimer, & Lewis, 2002).

Subjective health assessments are rooted in individuals' health beliefs and broader social factors (i.e. predisposing and enabling characteristics), and are linked to use or underuse of health services, including CP services (Glanz et al., 2002; Janz & Becker, 1984). In fact, the Health Belief Model (HBM) outlines the role of health beliefs in shaping individuals' adoption of healthy behaviors and use of preventive services (Becker, 1974; Glanz et al., 2002; Rosenstock, 1966). According to the HBM, there are four main health beliefs that shape individuals' use of preventive services: perceived susceptibility, perceived severity, perceived benefits, and perceived barriers (Becker, 1974; Glanz et al., 2002; Rosenstock, 1966; Rosenstock, 1974). Perceived susceptibility refers to individuals' beliefs about how vulnerable they are to a particular illness (Rosenstock, 1966). Perceived severity refers to individuals' beliefs about the seriousness and consequences of contracting the illness (Rosenstock, 1966). Perceived benefits refer to individuals' beliefs about efficacy of the recommended health behavior and potential benefits associated with the health behavior (Rosenstock, 1966). Perceived barriers refer to individuals' beliefs about the potential costs, tangible and psychological, associated with the health related behavior (Rosenstock, 1966). Thus, the impact of subjective health assessment on individuals' use of CP services may in fact be a reflection of their health beliefs, particularly beliefs about perceived severity and perceived susceptibility to illness. In this way, Andersen's behavioral model incorporates aspects of the HBM to understand the multiple determinants of health.

Andersen's (1995) behavioral health model was initially designed to predict individuals' use of physician services, ambulatory services, and dental services, but has since been extended to include a wide variety of health utilization outcomes such as adherence to recommended prescription drug regimens, access to substance abuse treatment, and use of recommended CP services such as mammography (Andersen, 1995; Rahman, Dignan, & Shelton, 2005). Interestingly, given the spiraling health care costs in the current environment, the model has been criticized for presuming that greater health services use is beneficial (Andersen, 1995). As Andersen (1995) points out, however, the model was developed at a time when health services underuse was the primary concern. In this respect, the model is ideal to examine underuse of CP services.

It is important to note that most preventive services use is distinguished from required clinical treatment because it is discretionary. Thus, there are differences in the contribution of predisposing, enabling, and need factors based on the nature of the healthcare service examined. Discretionary health behaviors are primarily the result of predisposing and enabling factors, while non-discretionary behaviors are driven primarily by clinical need (Andersen, 1995; Rosenstock, 1974; Glanz et al., 2002). This, coupled with HBM, has implications for CP service use. It is possible, for example, that individuals in good health may not feel it necessary to obtain recommended CP services because they may not feel susceptible to illness and/or may not believe that illness will be severe if they do get ill.

The advantage of using the Andersen's behavioral health model is that it provides a foundation to guide study on both the individual and contextual factors that impact individuals' use of CP services. It also provides the flexibility to incorporate tenets of the HBM, allowing for the inclusion of health beliefs in shaping health behaviors and healthcare use. Existing studies have used the model to guide research on a range of health outcomes, both discretionary and non-discretionary (Glanz et al., 2002). The model has been used, for example, to predict some types of CP service use, including influenza vaccinations (Rangel et al., 2005; Xu, 2002), colorectal cancer screening (Honda, 2004; Lee, 2011), mammograms (Vyas et al., 2012; Xu, 2002), and blood cholesterol screening (Xu, 2002).

Collectively, these theoretical frameworks provide important information on the individual and contextual characteristics that must be taken into account when examining individuals' use of CP services.

Chapter Three: Economic Conditions and Health

Although the majority of studies examining individuals' use of CP services have focused on individual-level factors, there are a number of studies that examine how contextual-level economic conditions shape individuals' use of CP services. Contextual-level economic conditions can be included as components of the external environment highlighted in the most recent revision of Andersen's (1995) behavioral model. Not surprisingly, existing studies demonstrate links between contextual-level economic conditions and health, health behaviors, and health services use, including CP services.

The next section focuses specifically on reviewing the existing literature on contextual-level economic conditions and CP service use. Because there is relatively little research that examines how contextual-level economic conditions affect individual-level CP service use, I rely mostly on studies that examine the relationships between economic conditions and general health, particularly health behaviors. Individuals' decisions to practice positive health behaviors are very similar to decisions to use CP services in a number of ways. First, investments in positive health behaviors, similar to investments in CP services, are likely to improve individuals' overall health (Glanz et al., 2002; Grossman, 1972). Moreover, CP services are similar to health behaviors because individuals do not commonly make the decision to access these services under duress. Typically, individuals' use of CP services is not the result of injury or illness, but as a way to prevent future health problems[2]. Thus, most CP service use is discretionary by

[2] In this respect, blood cholesterol screening occupies both a preventive function as well as a disease management function. That is, individuals with no history of illness are recommended to receive blood cholesterol screening every five years, but once

nature and represents an investment in future health (Andersen, 1995; Glanz et al., 2002; Grossman, 1972). That is, similar to other types of health behaviors such as physical activity, these are not pressing services that individuals must access immediately in order to avert an adverse health condition[3].

In this chapter, I review the existing literature on economic conditions and health, specifically focusing on the role of unemployment and income inequality. I conclude by identifying three pathways that may shape the relationships between economic conditions, health, health behaviors, and health utilization.

A number of studies examine the links between contextual-level economic conditions and health, including health behaviors and health utilization. In fact, a growing body of research suggests that state-level unemployment and income inequality affect health, though the direction and magnitude of the association differs based on the health outcome under study and the economic measures employed. Because adoption of healthy behaviors closely parallel individuals' decisions to obtain CP services, I pay specific attention to studies that examine the relationship between contextual-level economic conditions and health behaviors. There are only a handful of studies that examine the relationship between contextual-level economic conditions and individuals' use of CP services. I review these studies in detail.

Before reviewing the relevant literature, however, it is necessary to note that research in this area employs various methodological designs. Some studies focus

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individuals are at risk for heart problems and/or other chronic conditions, cholesterol screening is viewed as part of chronic disease management.

[3] CP Services are also different from health behaviors in a number of ways. They are received in a clinical setting and require individuals to make contact with the health system. They also require individuals to confront anxieties related to the possibility of positive test results.

exclusively on individual-level relationships while others examine contextual-level relationships in purely an ecological manner (e.g. state-level unemployment rates used to predict state-level health outcomes). Research studies that examine how contextual-level factors impact individual-level outcomes usually employ fixed effects analysis using pooled cross-sectional data or multilevel models using cross-sectional data. These studies are particularly important because they elucidate the relationships between contextual-level factors and individual-level outcomes, while controlling for individual-level characteristics. Studies that use micro level designs (i.e. individual-level correlates predicting individual-level outcomes) do not examine how contextual-level factors affect individual-level outcomes (Roux, 2002). On the other hand, studies employing purely ecological designs have limited applicability to individuals because of the ecological fallacy, which states that relationships found at the contextual-level may not be present at the individual-level (Robinson, 1950).

This study aims to understand how contextual-level conditions affect individual-level outcomes. Consequently, when possible, I focus on studies that employ mixed models with contextual-level characteristics predicting individual-level health outcomes, either using cross-sectional, longitudinal, or time-series data. Studies that employ multilevel models have the added advantage in that they take into account the correlated error structure that is characteristic of nested data (Raudenbush & Bryk, 2002). Finally, it is important to note that lagged measures of unemployment rates and income inequality are necessary to capture associations between economic conditions and health. Thus, many of the studies reviewed below use at least one year lags for unemployment rates and between one to fifteen year lags for income inequality[4].

Unemployment Rates and Health

Since Durkheim's (1897; 2013) seminal study, *Suicide*, where he identified links between economic conditions and suicide rates, many studies have examined the effects of contextual economic conditions on a variety of health outcomes and behaviors. Interestingly, although a large body of research documents the detrimental health effects of individual-level unemployment on individual-level health outcomes, the relationship between macroeconomic conditions and broader indicators of population health (e.g. mortality and self-rated health) remains ambiguous. Some studies find positive associations between macroeconomic conditions and population health outcomes, others find negative relationships, and still others find no relationship (Azriizumi & Schirle, 2012; Dehejia & Lleras-Muney, 2004; Miller, Page, Stevens, & Filipski, 2011; Ruhm, 2000; Subramanian, Kawachi, & Kennedy, 2003). Not surprisingly, many researchers are critical of this body of research, cautioning that these are macro level studies that predict population health outcomes so they have limited applicability to individuals. In spite of these concerns, a major contribution of this body of ecological research is that it has motivated researchers to examine the relationship between state-level unemployment rates and individual-level health outcomes, health behaviors, and health utilization. While this body of research is not directly related to the current study, it is nonetheless important for this reason.

[4] This is because income inequality often takes about ten to fifteen years to affect health (Blakely et al., 2000).

Unemployment and Health Behaviors

There is an expanding literature that documents the relationships between contextual-level unemployment rates and a variety of individual-level modifiable health behaviors such as alcohol use, nutritional intake, smoking, and physical activity (Ruhm, 2000; Ruhm, 2003; Dee, 2001). These studies use time series analysis over periods of ten to fifteen years, employing fixed effects models that control for time and state-level heterogeneity. To date, results have been ambiguous. Some research indicates there are increases in adverse health behaviors (e.g. reduced levels of physical activity, greater incidence of smoking, and poor nutritional intake) when unemployment rates are low, and a decrease in these behaviors when unemployment rates are high (Ruhm, 2000). However, other studies find that unhealthy behaviors increase when contextual-level unemployment rises (Miller, 2009; Dee, 2001). For example, existing research suggests that high contextual-level unemployment rates are linked to greater alcohol consumption, and reduced physical activity (An and Liu, 2012; Dee, 2001). In their study, An and Liu (2012) use the Behavioral Risk Factor Surveillance System to examine the relationship between county-level unemployment rates and individual-level physical activity over a twenty year period. Using pooled time series methods, they find that during times of high unemployment, individuals spend less time engaging in physical activity (An & Liu, 2012).

Unemployment and health services use. While there is a large body of research that examines the relationships between individuals' employment status and health utilization, only a handful of studies examine the relationships between broader contextual-level unemployment rates and individual-level health utilization such as CP service use. The studies that are available use pooled cross-sectional data and time series methods to examine the effect of macroeconomic conditions (e.g. state-level unemployment rates) on individuals' use of health services.

McInerney & Melor (2012) use individual-level data from the Medicare Current Beneficiary Survey (MCBS) along with state-level unemployment rates to examine how patterns of health services use vary among older individuals. Findings suggest that the elderly are more likely to report poor health status when unemployment rates are high, and are also more likely to use healthcare services. Ruhm (2000) uses a nationally representative sample of the U.S. population to examine the relationships between macroeconomic conditions at the state-level and individuals' use of health services (e.g. regular checkups, mammograms, digital rectal exams, pap smears). He finds no significant relationship between state-level unemployment rates and individuals' use of health services. However, he cautions that the sample size is low and lack of significant findings should be interpreted with caution. More recently, Tefft and Kageleiry (2013) pool cross-sectional data from the Behavioral Risk Factor Surveillance System over a longer period to examine the relationship between state-level unemployment rates and individuals' overall use of seven CP services, including mammograms, pap smears, colorectal cancer scope exams, prostate-specific antigen tests, digital rectal exams, and annual checkups. They also examine individuals' use of preventive services by measuring whether participants use any of the recommended services listed above. Their study pools together data from several different recessionary periods. Findings indicate that state-level unemployment rates are associated with an overall reduction in individuals' use of total CP services.

In light of these findings, there is an ongoing need for research to better understand how unemployment affects health and health utilization, including CP service use. Many of the available studies use cross-sectional data pooled over a large period of time. While this is beneficial in that it allows researchers to control for time and state-level heterogeneity, there are some concerns that the time period analyzed in these studies may be driving results (Pacula, 2011). Indeed, many of the relevant current studies have employed data from the less severe recessions in 1990 and early 2000 (c.s.Ruhm; 2000). Additionally, these studies do not examine individuals' use of blood cholesterol screening. To further complicate matters, the studies that do examine the relationship between state-level unemployment and individual-level CP service use have produced mixed findings. The current study fills this gap by examining how state-level unemployment rates affect individuals' use of three specific CP services, influenza vaccinations, blood cholesterol screening, and endoscopic colorectal cancer screening.

Income Inequality and Health

Research documents links between contextual-level income inequality and health, but isolating the effects of individual-level income and contextual-level income inequality has proven to be difficult (Lynch et al., 2004; Subramanian & Kawachi, 2003). Broadly, existing research finds significant associations between contextual-level income inequality and population health outcomes such as mortality. The majority of studies employ ecological designs that examine the effect of contextual-level income inequality on overall mortality rates. To date, findings have been mixed and controversy is ongoing. Specifically, many argue that the relationships at contextual-levels are a function of material resources at the individual-level (Clarkwest and Jecks, 2003). A few studies have taken into account individual-level income and other material resources to determine whether contextual income inequality exerts a significant effect on health net of the effect of individual-level income. Some studies report significant negative effects of income inequality on health (Lopez, 2004; Kondo et al., 2009), while others find no relationship (Sturm & Gresenz, 2002). Thus, the issue remains far from settled. However, this body of research has spurred research on the relationship between income inequality and other types of health outcomes, including health behaviors and health utilization.

Income Inequality and Health Behaviors

A growing body of research examines the relationship between contextual-level income inequality and individuals' modifiable health behaviors such as nutrition, physical activity, smoking, and alcohol use. Many of these studies use multilevel models and control for individuals' socio-economic and demographic characteristics. Broadly, this body of research finds that higher income inequality is associated with greater likelihood of individuals engaging in risky health behaviors, while lower income inequality is associated with individuals practicing positive health behaviors. For example, a study by Diez-Roux, Link, and Northridge (2000) examines the relationship between state-level income inequality and individuals' cardiovascular disease risk factors (BMI, hypertension, sedentarism, and smoking). Using a representative sample from the United States, Diez-Roux and colleagues (2000) employ multilevel models to estimate this relationship. Findings suggest that state-level income inequality is associated with increased risk of BMI, hypertension, and sedentary behavior for men, but not for women.

Another study by Elgar and colleagues (2005) examines the relationship between contextual-level income inequality and frequency of drunkenness among adolescents across thirty-four countries. Using multilevel logistic regression, findings reveal that young adolescents residing in areas with higher income inequality are more likely to consume alcohol. In another study, Subramanian, Kawachi, and Smith (2007) employ multilevel models to examine the relationship between contextual-level income inequality and nutritional intake in India. Findings suggest that a one standard deviation increase in income inequality increases the odds of being underweight and overweight.

Income Inequality and Use of CP Services

Although studies examining the relationships between individuals' socioeconomic characteristics and use of CP services are plenty, to my knowledge, there are no studies that examine the relationships between state-level income inequality and individuals' use of CP services. The studies that are available employ purely ecological designs or purely individual-level designs. Studies employing ecological designs find that contextual-level income inequality shapes population coverage rates for some CP services. Nagaoka, Fuijiwara, and Ito (2012), for example, examine the relationship between municipal income inequality and measles vaccination coverage rates in Japan. They find that higher income inequality is associated with lower measles vaccination coverage rates. In another study, researchers examine return rates of FOBT, which is used to detect colorectal cancer, from residents across different areas in the United Kingdom (Von Wagner, Good, Whitaker, & Wardle, 2010). They find that in spite of providing testing kits, individuals from the most economically deprived areas are the least likely to return kits. They note that "the gradient in participation is particularly striking because the

FOBT kit is delivered routinely every two years directly to the home at no cost to the individual, the test is self-administered, and the kit is returned in prepaid envelope, all features that would appear to overcome the barriers of time, cost or contact with health professionals" (Von Wagner, et al., 2010; pg. 136).

While there are no studies that examine the relationships between contextual-level income inequality and individuals' use of CP services, there are a handful of studies that examine the relationship between contextual-level income inequality and illnesses that can be prevented or detected at earlier stages if CP services are utilized. These studies employ mixed model designs. For example, Heck & Gorin (2004) examine the relationship between neighborhood-level socioeconomic differences and breast cancer stage at diagnoses using a mixed model approach. They pool data from 1992 to 1998 from the Surveillance, Epidemiology, and End Result (SEER) program and link it to individual-level Medicare data. Results reveal that individuals residing in relatively disadvantaged areas have higher odds of breast cancer, at every stage. Moreover, even after controlling for health insurance, individuals residing in neighborhoods with higher income inequality are more likely to be diagnosed at a later stage. Another study by Anderson, Yang, and colleagues (2014) examines the relationship between economically deprived counties in the Applachian Region in the U.S. and stage of breast cancer diagnoses. They find that women residing in economically deprived areas are more frequently diagnosed with later stages of breast cancer than their counterparts living in less deprived areas. Moreover, they find that women in more disadvantaged areas are also less likely to adhere to recommended screening schedules.

The studies that employ mixed designs do not examine the relationship of state-level income inequality on individuals' use of influenza vaccinations, blood cholesterol screenings, or endoscopic colorectal cancer screenings. In fact, the studies that are available employ ecological or individual-level designs that are not appropriate for understanding how contextual conditions shape individuals' use of CP services. The existing research does not directly estimate the association between contextual income inequality and individuals' use of CP services. This warrants further investigation using multilevel modeling where the contextual effects of income inequality on individuals' use of CP services can be parsed from the effects of individual-level income. Currently, to my knowledge, there are no studies that employ a multilevel framework to understand the role of state-level unemployment rates and income inequality on individuals' use of influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screening.

Pathways Linking Economic Conditions and Healthcare Use

Researchers identify several mechanisms through which economic conditions can affect health and healthcare use. First, high unemployment rates create tangible financial barriers (e.g. low income, loss of health insurance) as people take lower paying jobs and/or grapple with underemployment (Chapin & Reschovsky, 2012). The same is true for income inequality, particularly for people on the lower end of the income spectrum. Consequently, some researchers argue that individual-level resources (e.g. employment status and annual household income) drive the association between income inequality and health (Lynch & Kaplan, 1997; Lynch, Smith, Kaplan, and House, 2000). This hypothesis is commonly termed the materialist perspective. Thus, studies that aim to understand how economic conditions affect health, health behaviors, or health utilization, must take into account the effect of individual-level material resources that affect individuals' use of health services.

The effects of economic conditions on health may not function merely through individual-level material resources. It is also possible that residing in areas with higher unemployment and income inequality shapes individuals' health and health behaviors through a variety of intervening mechanisms, both individual- and contextual-level.

To date, a number of hypotheses have been offered to explain how contextual-level unemployment rates affect health and healthcare use. Quinn and colleagues (2009) postulate that individuals residing in areas with high unemployment may be distracted from taking care of their health (Quinn, Catalano, and Felber, 2009; Catalano, Satariano and Ciemins, 2003). They argue that although not everyone in a community experiences job loss, the threat of unemployment is still pervasive in areas with high unemployment (Catalano & Satariano, 1998; Catalano et al., 2003). Catalano and colleagues (2003) explain that stressful economic conditions can distract people from engaging in healthy behaviors, thus having a negative effect on individuals' health related behaviors. On the other hand, Ruhm (2000) postulates that there may be a positive relationship between unemployment rates and health. He explains that individuals may be less likely to adopt positive health related behaviors when economic conditions are favorable because of limited leisure time and/ or higher opportunity cost of time. From this perspective, individuals may be less likely to use time-intensive health services when unemployment rates are low, and more likely to do so when unemployment rates are high (Ruhm, 2000).

It is also possible that contextual-level unemployment shapes individuals' risk propensity. Individuals may be more willing to take chances with their health when unemployment rates are low, and less willing to do so when unemployment rates are high (Ruhm, 2000). Thus, the direction of the relationship between unemployment rates and CP service use can be positive or negative, depending on underlying pathways.

Researchers have put forth similar hypotheses to explain how income inequality can affect health and health related behaviors. Moss, Thaker, and Rudnick (2013) explain that individuals residing in areas with higher income inequality may have different decision-making and behavioral patterns than individuals residing in more egalitarian areas (Moss et al., 2013). Drawing off the economics and behavioral psychology literature, Moss and colleagues (2013) explain that, "inequality influences individuals' degree of optimistic bias or their perceptions of risk and their appetite for risk taking" (Moss et al., 2013, pg.2). This, in turn, may affect individuals' health and health related behaviors. Relatedly, the relative income hypothesis suggests that area-level income inequality can affect health and health behaviors by influencing individuals' psychosocial processes (Wilkinson, 1996). According to the relative income hypothesis, individuals living in areas with greater income inequality may feel frustrated and stressed, and this may shape health and health behaviors (Wilkinson, 1996; Wilkinson & Pickett, 2011).

Additionally, existing research posits that contextual-level intervening mechanisms may also partially shape the relationship between economic conditions and health, and may possibly shape individuals' use of CP services, as well. The social capital perspective suggests that economic conditions affect social capital, and social capital, in turn affects health related behaviors (Lynch et al., 2000). Social capital is a community trait that can best be described as the "features of social organization, such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit" (Putnam, 1995, pg. 67). Existing research suggests that societal income inequality erodes social capital (Berkman & Kawachi, 2000). Employment relies crucially on social networks and social capital so there is reason to believe that unemployment may erode social capital as well (Dieckhoff & Gash, 2013; Nichols, Mitchell, and Lindner, 2013). There is a growing body of research that links social capital to a variety of health behaviors, including individuals' use of CP services. These studies will be explored in the next chapter.

Area-level resources may also partially explain the association between economic conditions and health (Lynch et al., 2000). This hypothesis, termed the neo-material perspective, suggests that disadvantaged economic areas such as those characterized by high unemployment rates and/or greater income inequality have fewer resources (Lynch et al., 2000; Martin et al., 2011). This may happen, for example, when states with high unemployment are faced with fiscal shortages and limited reserves; response to such conditions usually include cutting a variety of health and social spending programs (Johnson, Oliff, & Williams, 2011). Similarly, in areas with high-income inequality, area-level resources may be depleted because the interests of those with financial resources are distinct from those of the poor, and those with greater financial resources exert more influence on statewide policies and investments (Kawachi, Kennedy, Lochner, & Prothrow-Stith, 1997; Kawachi, Kennedy, & Glass, 1999; Moss et al., 2013). Indeed Moss et al., (2013, pg. 3) note that "if high inequality is associated with imperfect capital markets, human capital investments will generally be limited to those in the upper parts of the income distribution, which in turn implies that the distribution of resources will affect aggregate investment in human capital . . ."

Collectively, these intervening mechanisms may partially mediate the association between economic conditions and CP service use. They will be explored in detail in the next chapter.

Summary

This chapter examines the relationship between contextual economic conditions, assessed by unemployment and income inequality, and health. Broadly, the existing literature links contextual-level unemployment and income inequality to individuals' health behaviors, though findings depend largely on the health outcome examined. There is sufficient evidence at the ecological level to suggest that broader economic conditions play a role in shaping individuals' use of health care services, including CP services. Despite this, there is very little research that examines the relationship between contextual-level economic conditions (e.g. unemployment rate and income inequality) on individuals' use of CP services. Specifically, there are only a handful of studies that examine the relationship between unemployment rates and individuals' use of CP services, and none that examine the relationship between unemployment rates and individuals' use of blood cholesterol screening. Moreover, the research that is available yields mixed findings so further research is necessary. There are also no studies that examine the relationships between contextual-level income inequality and individuals' use of CP services. The studies that are available employ ecological or purely individual-level designs that are not appropriate for estimating how broader income inequality affects individuals' use of CP services.

The studies that are available suggest that contextual-level economic conditions may have affect individuals' health and health behaviors by affecting individuals' material resources (e.g. income). Alternatively, broader economic conditions may also affect individuals' decision-making and behavior. There are also two major contextual-level explanations that suggest economic conditions may impact social capital and the availability of area-level resources. These social factors, in turn, may play a role in shaping individuals' use of CP services. I discuss these perspectives in detail in the next chapter.

Chapter Four: Social Conditions and Health

Existing research suggests that many social conditions affect health, health behaviors, and healthcare use. I focus on two contextual-level perspectives that may partially shape the relationships between economic conditions and health, the social capital perspective and the neo-material perspective. These perspectives suggest that social capital and area-level resources play a role in shaping health and health related behaviors (Kawachi, Subramanian, & Kim, 2008; Lindstrom & Lindstrom, 2006; Macinko & Starfield, 2001; Veenstra, 2000). In fact, existing research finds that social capital is associated with various health outcomes, health behaviors, and some types of health utilization. There is also a growing body of literature that links neo-material resources, which are essentially area-level resources, to health and health behaviors. Indeed, both the social capital and neo-material perspectives may exert an influence on health and health related behaviors. In fact, the presence of social capital may increase the availability of area-level resources (Kawachi, Takao, & Subramanian, 2013; Lindstrom & Lindstrom, 2006). The opposite may also be true where the presence of some types of area-level resources may increase some elements of social capital such as social networks and trust (Van Damme et al., 2010). These mechanisms may partially explain how economic conditions shape individuals' health and health related behaviors, including CP service use. Indeed, under Andersen's (1995) behavioral health model, these contextual factors can be considered enabling features of the environment that shape individuals' use of CP services.

In the following section, I review the existing theoretical and empirical literature on social capital and neo-material resources. Specifically, I examine the empirical research linking each approach to health and healthcare use, and the pathways through which these effects operate. Interestingly, much of the research in this area relies on cross-sectional individual-level analyses. However, there are a number of studies that employ multilevel analysis to account for the hierarchical nature of the data. I review these studies in detail.

Social Capital

Social capital is a broad concept that captures the "features of social organization, such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit" (Putnam, 1995, pg. 67). It has also been defined as a "web of cooperative relationships between citizens that facilitate resolution of collective action problems" (Brehm & Rahn, 1997, pg. 999). Because social capital is a multidimensional construct, researchers have employed a number of indicators to capture the presence of social capital in a community. Commonly used measures include individuals' involvement in various voluntary associations and groups, trust and confidence in various aspects of society, willingness to exchange favors with others in their neighborhood, individuals' degree of sociability, and/or quality of social networks. A detailed review of the conceptualization and measurement of social capital will be provided in Chapter Five.

Social Capital and Health

Existing research documents the links between social capital and health. A growing body of literature finds that greater social capital is positively associated with health, health behaviors, and some types of health care utilization. Before reviewing the relevant literature, however, it is important to note that social capital is present within complicated networks of relationships and there is a large body of research that suggests it is appropriately captured at a contextual-level (Kawachi et al., 2013; Putnam, 1995). Thus, researchers often aggregate individual-level responses to larger geographical units[5]. Unless otherwise noted, the studies reviewed below use aggregate measures of social capital.

Social capital and health outcomes. A large body of research examines the relationships between social capital at the contextual-level (state, county, or neighborhood) and population health indicators such as mortality and self-rated health. Indeed, much of the interest in social capital and health behaviors stems from seminal studies that employ purely ecological designs to examine the link between social capital and mortality. Existing research suggests that areas with greater social capital have lower mortality rates (Kawachi, Kennedy, Lochner, and Prothrow-Smith, 1997; Lochner, Kawachi, Brennan and Buka, 2003). Other studies find links between contextual-level social capital and self-rated health, both in the United States and abroad using multilevel study designs (Subramanian, Kim and Kawachi, 2002; Poortinga, 2006; Snelgrove, Pikhart and Staffort, 2009). Generally, these studies find that some indicators of social capital, particularly social trust and involvement in associations and groups, are associated with better self-rated health even after controlling for individual-level socio-demographic characteristics. These and related studies have sparked interest in

[5] In his works, for example, Putnam (2001) measures the degree of social capital in a community by examining aggregate indicators of voter turnout, newspaper readership, etc. In their work, Kawachi and colleagues (1995) create aggregate measures of social capital by summing responses to social capital indicators across states.

understanding how social capital affects other aspects of individuals' health, including health behaviors and healthcare use.

Social capital and health behaviors. Generally, the existing research suggests that there are positive associations between social capital and a number of health behaviors. Specifically, research shows that some aspects of social capital are important in predicting individuals' health behaviors. In one study, Mohnen, Volker, Flap, and Groenewegan (2012), for example, use multilevel models to examine whether modifiable individual-level health behaviors (smoking, alcohol consumption, nutritional intake, sleep duration, and physical activity) are associated with neighborhood social capital among a Dutch sample. They construct a scale of neighborhood social capital to assess neighborhood sociability, friendliness, and reciprocity, measured by asking respondents if they are friends with their neighbors and whether they would be comfortable asking their neighbors for favors. Findings suggest that there are positive links between neighborhood social capital and individuals' physical activity and non-smoking behavior. Other studies report similar results, finding that greater contextual-level social capital, commonly measured by trust and different types of social and civic participation, is associated with positive individual-level health behaviors including improved nutrition and lower risk of binge drinking (Lindstrom et al., 2003; Mohnen et al., 2012; Weitzman and Kawachi, 2000). Yet, in their study, Lindstrom, Moghaddassi, & Merlo (2003) do not find links between social capital and physical activity among a Swedish sample.

Although they employ multilevel models, they use a contextual-level measure for social capital, residential mobility, which is not commonly used in the literature[6].

Social capital and health utilization. Existing research outlines the links between social capital and some types of health utilization, but findings vary based on type of health service utilization examined. Laporte, Nauenberg, and Shen (2008), for example, use semi-parametric methods to examine the relationships between community-level social capital and individual-level physician visits and hospitalizations among older individuals. They use the Petrix Social Capital Index (PSCI) that assesses social capital based on employment in various religious and community-based organizations. Findings suggest that community social capital is associated with lower likelihood of physician visits, but higher likelihood of hospitalization. In another study, Nauenberg, Laporte, and Shen (2011) use the PSCI to examine how community-level social capital affects individuals' health utilization. They find that higher community social capital is associated with less frequent physician visits. Samek (2010) uses the PSCI as well as proxy measures for individual-level social capital (e.g. sense of belonging in the community, religious attendance, and marital status) to examine how social capital affects immigrants' use of health services. Findings suggest that individuals with higher feelings of community belonging have fewer physician visits.

Thus far, there are only a handful of studies that explore the relationships between social capital and CP service use. These studies use purely ecological or individual-level designs. Moreover, some studies measure social capital at a contextual-level, while others use individual-level indicators of social capital. Because there are no studies that

[6] While neighborhood mobility does reflect the stability of a neighborhood, it has not been widely used as a key measure of social capital.

employ mixed model designs, I draw off this literature to better understand how social capital affects CP service use. It is necessary to note that this body of research cannot assess how contextual-level social capital affects individuals' use of CP services. To my knowledge, there are no multilevel studies that examine the relationship between social capital and individuals' use of influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screenings.

There are three studies that examine the relationships between social capital and CP services. These studies employ pure ecological or individual-level designs. Nagaoka, Fujiwara, and Ito (2012) examine the relationship between social capital, measured by volunteering rates and voting rates, and measles coverage rates in Japan using a pure ecological study design. They find that volunteering rates are significantly associated with greater measles-vaccine coverage. Moudatsou, Kritsotakis, Alegakis, Koutis, and Philalithis (2014) examine the relationship between individual-level social capital and women's use of breast and cervical cancer screening in a rural area of Crete. They ask a random sample of women questions about their participation in the community, connections with friends and family, and adherence to breast and cervical cancer screening recommendations (Moudatsou et al., 2014). Findings suggest that individual-level social capital indicators are salient in predicting adherence. Leader and Michael (2013) examine the relationship between individual-level social capital and individuals' use of cervical, breast, and colon cancer screening. They measure social capital by asking respondents about involvement in local groups or organizations, feelings of belonging, and neighborhood trust. They find weak but positive associations between measures of social capital and screening use.

A few individual-level studies examine the relationship between trust, one of the elements of social capital, and individuals' use of CP services. These studies do not incorporate other dimensions of social capital and they measure trust at the individual-level. Nonetheless, these studies provide important insights into the relationship between social capital and CP service use because trust is a fundamental element of social capital (Putnam, 2001). Overall, findings suggest that trust is an important component of healthcare use, and an especially important determinant of individuals' use of CP services. For example, Musa, Schulz, Harris, Silverman, and Thomas (2009) use a cross-sectional sample of older adults from Pennsylvania to examine how trust in physicians, medical research, and health information sources affects use of some types of CP services, measured by recommended use of influenza vaccinations, mammograms, prostate specific antigen (PSA) tests, and routine health checkups. Findings suggest that trust is associated with higher odds of obtaining mammograms, routine health checks, and PSA tests. Another study by Yang, Matthews, and Hillemeier (2011) examines the relationship between individual-level distrust in the health care system and women's use of breast and cervical cancer screening. Findings suggest that women who report high levels of distrust in the healthcare system are less likely to obtain breast and cervical cancer screening. The researchers caution that distrust in the health care system may serve as a barrier to CP service use (Yang et al., 2011). Another study by Yang, Matthews, and Anderson (2013) examines the relationship between distrust of the healthcare system and prostate cancer screening among older men (ages 45 to 75 years). Findings suggest that men who report greater distrust in the health care system are less likely to have prostate cancer screenings (Yang et al., 2013).

A few studies also examine the relationships between individual-level trust in the media and individuals' healthcare use, including use of CP services. McQueen, Vernon, Meissner, Klabunde, and Rakowski (2006) examine gender differences in the use of colorectal cancer screening using data from the 2002-2003 Health Information National Trends Survey (HINTS). They find that for men, there is a significant association between trust in media and recommended use of sigmoidoscopy and colonoscopy, but not FOBT. This is not surprising since sigmoidoscopy and colonoscopies are invasive medical procedures, but FOBT is relatively non-invasive. Grilli, Ramsay and Minozzi (2002) review twenty studies that examine how the media shapes individuals' use of health services, including some types of CP services (e.g. immunizations and screenings). Although they are cautious about the quality of the research, they conclude that the media is a key player in promoting prevention behaviors and use of preventive services (Grilli et al., 2002). In fact, Grilli and colleagues (2002, pg. 7) conclude that because the media plays such a critical role in the dissemination of health related information and promotion of preventive healthcare, efforts should be made to ensure that "reporting of health related issues in the lay media correctly represents the best available knowledge on the effectiveness of health care interventions."

Overall, these studies suggest that elements of social capital play a key role in shaping individuals' health, health behaviors, and health utilization. However, there are very few studies that examine the relationship between social capital and CP service use, and none, to my knowledge, that do so using a multilevel framework. Existing studies employ individual-level measures of social capital and/or ecological study designs that are unable to assess the impact of contextual-level social capital on individuals' use of CP services. Thus, further research is necessary to better understand how contextual-level social capital shapes individuals' use of CP services.

Pathways Linking Social Capital to Health

Medical sociologists postulate that social capital may affect health through several mechanisms. Kawachi and colleagues (2008) explain that living in areas with high social capital may encourage individuals to adopt healthy behaviors if the behavior is an established norm in the community. For example, individuals residing in areas with high social capital may be more likely to obtain influenza vaccinations if most residents obtain influenza vaccinations. Some researchers postulate that social capital may affect health and health behaviors by limiting deviant behavior (Kawachi et al., 2008). While this may be true for some types of modifiable health behaviors (e.g. alcohol misuse and smoking), it is less likely to be relevant for CP service use; foregoing CP services is not generally viewed to be a deviant act. It is possible, however, that if public attitudes towards some types of CP services are overwhelmingly negative, then higher social capital may reduce individuals' likelihood of obtaining CP services. (This is unlikely, however, because there is no evidence to indicate that public attitudes towards CP services are overwhelmingly negative.)

Another pathway through which social capital can affect health is through information flow. This hypothesis, grounded in Rogers' (1993) diffusion of information theory, states that the elements of social capital (e.g. civic and social participation) create environments that foster communication (Kawachi et al., 2008). When applied to CP service use, this suggests that environments with greater social capital resources expose residents to health messages, including CP service recommendations. Thus, areas with higher social capital may improve flow of information, effectively increasing individuals' general knowledge of CP service recommendations (Kawachi et al., 2008). Indeed, Viswaneth and colleagues (2006) find that residents living in areas characterized by high involvement in community type associations have better recall of health related messages.

Social capital may also foster social and institutional trust. Existing research shows that individuals residing in areas with higher social participation report greater social trust (Putnam, 2001). In fact, trust is such a crucial component of social capital theory because it encourages the flow of information, and it is especially important in the current environment where people have access to health information from a variety of sources (Kawachi et al., 2008; Mechanic, 1998; Rowe & Calnan, 2008). Areas rich in social capital may not only have greater information flow, but also greater trust. This means, for example, that individuals residing in such communities may not only be aware of CP service recommendations, but also place greater trust in these recommendations, which in turn may make them more likely to use recommended CP services. Thus, some researchers postulate that individuals residing in areas with greater interpersonal trust may be more willing to adopt health promoting interventions (Berkman & Kawachi, 2000; Kawachi et al., 2013; Rostila, 2007). Not surprisingly, there are increasing calls for researchers to examine how trust in various institutions shapes health and healthcare use from a broader social capital perspective (Gilson, 2003; Mechanic & Alpine, 2010).

Finally, social capital can also affect health and CP service use by improving access to resources. This can be accomplished by increasing individuals' network of people who can provide material and other supportive resources. For example, living in areas with higher levels of social capital may allow residents to pool resources when necessary and exert collective influence (Kawachi et al., 2008). This means, for example, that individuals may be able to access reduced cost or free influenza vaccinations from local health departments. Areas rich in social capital may also be rich in health related resources that shape the use of CP services (Ogden, Morrison, and Hardee, 2013). Thus, social capital can actually improve health policy and health systems in a given area (Ogden, Morrison, and Hardee, 2013). I discuss the influence of area-level resources on health in the next section.

Existing research suggests that social capital can facilitate the adoption of health care messages, health strategies, and shape CP service use. Given the invasive and risky nature of many CP services, it is logical that certain elements of social capital (e.g. social and institutional trust) may be particularly important in shaping CP service use. However, to date, very little research examines the relationship between social capital and CP service use. Moreover, no studies employ multilevel models to understand how this social contextual feature of the environment shapes individuals' decisions to obtain CP services.

Neo-Material Perspective

According to the neo-material perspective, area-level resources may also play an important role in shaping individuals' health, and may partially explain the links between contextual-level economic conditions and individuals' health and healthcare use (Lynch et al., 2000). This perspective suggests that economically deprived areas often possess fewer area-level resources (Lynch et al., 2000; Oliff, Mai, & Palacios, 2007). In areas with high unemployment rates, for example, health care resources may become scarce as states cut health and spending programs to adjust to declining budgets (Johnson, Oliff, & Williams, 2011). In areas with high-income inequality, the interests of the wealthy, who typically have greater social, political, and economic influence, may be distinct from the poor (Kawachi et al., 2008). This may have cascading effects on the availability of healthcare resources (Pugh, 2012). Ultimately, this perspective suggests that there may be substantial material differences in resource availability as a result of differing contextual economic conditions, and these differences may shape individuals' health and health related behaviors, including CP service use.

There are numerous area-level resources that have direct and indirect impacts on health and health related behaviors. Because the current study focuses on the use of CP services, I limit this review only to studies that examine the relationship between healthcare supply and health services use. Specifically, I focus on primary care physician supply because primary care physicians are instrumental in informing individuals about CP service recommendations, ordering CP service screenings and/or providing referrals for CP services (National Institute for Health Care Reform, 2013). Primary care physicians are clinicians "who are accountable for addressing a large majority of personal health care needs, developing a sustained partnership with patients, and practicing in the context of family and community" (Donaldson, Yordy, and Vanselow, 1994, pg.1). They are usually the first point of contact that most adults make with the healthcare system so availability of primary care is intimately tied to issues of access to care (DHHS, 2008). However, recent data suggests that thirty-three states currently have or will have projected shortages of primary care physician supply (AAMC, 2012; Cunningham, 2011). This is especially true of rural locations and areas that are economically disadvantaged, including areas with high rates of unemployment (Chen et al., 2013). In the following section, I examine the existing research on the relationships between primary care physician supply, health, and health utilization. The majority of these studies use ecological study designs, but a few use mixed-level designs so I review these studies in detail.

Primary Care Physician Supply and Health Outcomes

Broadly, existing research on the relationship between primary care physician supply and health outcomes (e.g. mortality, health status; birth weight) suggests that greater primary care physician supply is associated with better health outcomes (Shi, 1992; Shi, 1994). Many studies find a positive relationship between primary care physician supply and a range of health outcomes, including all cause mortality, age and cause specific mortality, birth weight, and self-rated health (Shi et al., 2005a; Shi et al., 2005b). However, there are also some studies that find no relationship between primary care physician supply and health outcomes (Pierard, 2009). While these studies are not directly applicable to the current study because they focus on health outcomes, they have led to further research on the relationships between primary care physician supply, health behaviors, and health utilization.

Primary Care Physician Supply, Health Behaviors, and Health Utilization. Some studies examine the relationship between primary care physician supply and health related behaviors such as breast-feeding, abstaining from smoking, use of seatbelts, greater physical activity and better nutrition (Shi, 1994; Shi & Starfield, 2000). This body of research suggests that the availability of primary care physicians has positive effects on health related behaviors (Shi, 1994; Shi & Starfield, 2000; Starfield, Shi, & Macinko, 2005).

Some research studies the relationships between per capita primary care physician supply and use of cancer screening by examining data on the stage at which cancer is diagnosed. Roetzheim and colleagues (1999), for example, conduct an ecological study using data from sixty-seven Florida counties to examine whether primary care physician supply is associated with reduced colorectal cancer mortality. Results reveal that counties with higher supply of primary care physicians and general internists have greater odds of early stage diagnosis of colorectal cancer. Another study by Ferrante and colleagues (2000) finds that the same is true for breast cancer diagnoses. Other studies confirm these findings for other types of cancer screening (Campbell et al., 2003; Roetzheim et al., 2000)

To my knowledge, only two studies use multilevel models to examine the relationships between primary care physician supply and CP service use. Flocke, Stange, and Syzanski (1998) use a cross sectional sample of patients in Ohio to examine the relationship between primary care services and use of preventive services. Employing a multilevel model that controls for patient-level characteristics, they find that greater availability of primary care services is associated with appropriate and timely use of screenings and immunizations, as well as adoption of other healthy behaviors. Continelly, McGinnis, and Holmes (2010) examine the same topic using a multilevel dataset that includes individuals nested within zip codes among a New York sample. Preliminary results reveal that individuals residing in areas with more physicians are more likely to receive blood pressure, diabetes, and cholesterol screenings. They are also more likely to receive influenza vaccinations and blood stool tests. However, the effect of physician supply on preventive care use diminishes and eventually loses significance after incorporating individual-level health related variables (e.g. health status) (Continelly et al., 2010).

Since the findings from these two studies are mixed and no study to date examines the effects of state-level primary care physician supply on individuals' use of endoscopic colorectal cancer screening, research on this topic is necessary. Primary care physicians are the first point of contact that most individuals have with the healthcare system and they play an instrumental role in recommending and delivering many CP services (NIHCR, 2013). Similar to social capital, under Andersen's (1995) behavioral health model, primary care physician supply can be viewed as an enabling feature of the social environment that shapes individuals' use of CP services. The majority of existing research employs ecological or individual-level designs, and does not provide information on the relationships between contextual-level primary care physician supply and individuals' use of CP services. Thus, the need for further research on this topic is clear.

Pathways Linking Primary Care Physician Supply and Health

There are several ways through which primary care physician supply affects health and healthcare use. Research suggests that areas with greater primary care physicians have lower barriers to accessing care (Starfield, Shi, and Macinko, 2005). In fact, existing research suggests that areas with greater primary care physician supply have more equitable distribution of health and fewer health disparities, even in the presence of high-income inequality (Starfield et al., 2005). This is not surprising because primary care physicians are typically the first contact adults have with the healthcare system. They are also instrumental in informing individuals of health related recommendations and encouraging individuals to take steps to improve their health (Donaldson et al., 1994). It is also possible that the effect of greater primary care physician supply on use of CP services operates through reduced healthcare costs. Existing research suggests that greater general physician supply, as opposed to specialty physician supply, is associated with reduced health spending (Franks & Fiscella, 1998; Baicker & Chandra, 2004; Starfield, Shi, & Macinko, 2005). Thus, individuals residing in areas with greater supply of primary care physicians may spend less on their overall healthcare, leaving more funds for discretionary care such as preventive services. Finally, it is also possible that in areas with greater physician supply, there is greater communication and collaboration between physicians, thus leading to better coordination of care and quality of care for individuals (Highsmith & Bereenson, 2011).

Summary

This chapter reviews the theoretical pathways through which economic conditions can affect health and healthcare use, including CP service use. Despite the existing body of literature that outlines the links between economic conditions, social capital, neo-material resources, and health, there are few studies that examine how these contextual factors affect individuals' use of CP services. The studies that have looked at CP outcomes have done so using either individual-level or ecological study designs. These studies are not appropriate for understanding how broader economic and social factors impact individuals' use of CP services. Further research is necessary to examine how social capital and area-level health related resources such as primary care physician supply shape individuals' use of CP services.

Chapter Five: Conceptual Model, Aims, and Hypotheses

While the existing body of research suggests that there are links between contextual-level economic conditions and individuals' use of CP services, there remain a number of gaps in the literature. First, the relationship between economic conditions and CP service use has not been explored for all types of CP services. For example, to date, there are no studies that have examined the relationship between state-level unemployment rates and individuals' use of blood cholesterol screenings. Moreover, the studies that examine state-level unemployment rates and individuals' use of CP services do so by bundling together all relevant CP services. Additionally, studies do not examine the relationships between state-level income inequality and individuals' use of CP services, including influenza vaccination, blood cholesterol screening, and colorectal cancer screening. The studies that are available employ purely ecological designs or purely individual-level designs. These studies do not allow an understanding of how contextual-level economic conditions at the state-level shape individual-level CP service use outcomes.

Second, very few studies explore the various mechanisms through which economic conditions can affect health, and none that do so for the CP services examined in the current study. In fact, there are no current studies that examine the relationships between contextual social capital at the state-level and individuals' use of CP services. The studies that are available focus on the relationships between individual-level social capital and individual-level CP services (Leader and Michael, 2013). These studies do not examine how state-level social capital shapes individuals' use of influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screenings.

Finally, very few studies examine the relationship between state-level health related resources, specifically primary care physician supply, and use of CP services. While studies do examine the relationship between primary care physician supply, health behaviors, and health utilization including some types of preventive care use, only two focus on individuals' use of CP services within a multilevel framework. These studies report mixed findings. Other studies that are available employ purely ecological designs, smaller geographic areas, and/or focus only on individual-level factors. Thus, further research is necessary to better understand how state-level primary care physician supply shapes individuals' use of CP services.

The current study aims to fill these gaps. Specifically, I examine the effects of state-level unemployment rate, income inequality, social capital, and primary care physician supply on individuals' use of CP services, after taking into account a broad range of individual-level factors. Based on the Grossman's (1972) model of healthcare demand, Andersen's (1995) behavioral health model, and the existing literature, I develop a conceptual model and a set of research questions to guide the study. In this chapter, I present the overall conceptual model and the specific research questions for the current study. I also present the specific aims along with the associated hypotheses.

Conceptual Model

Based on the theoretical frameworks and the empirical literature, the following conceptual model has been developed

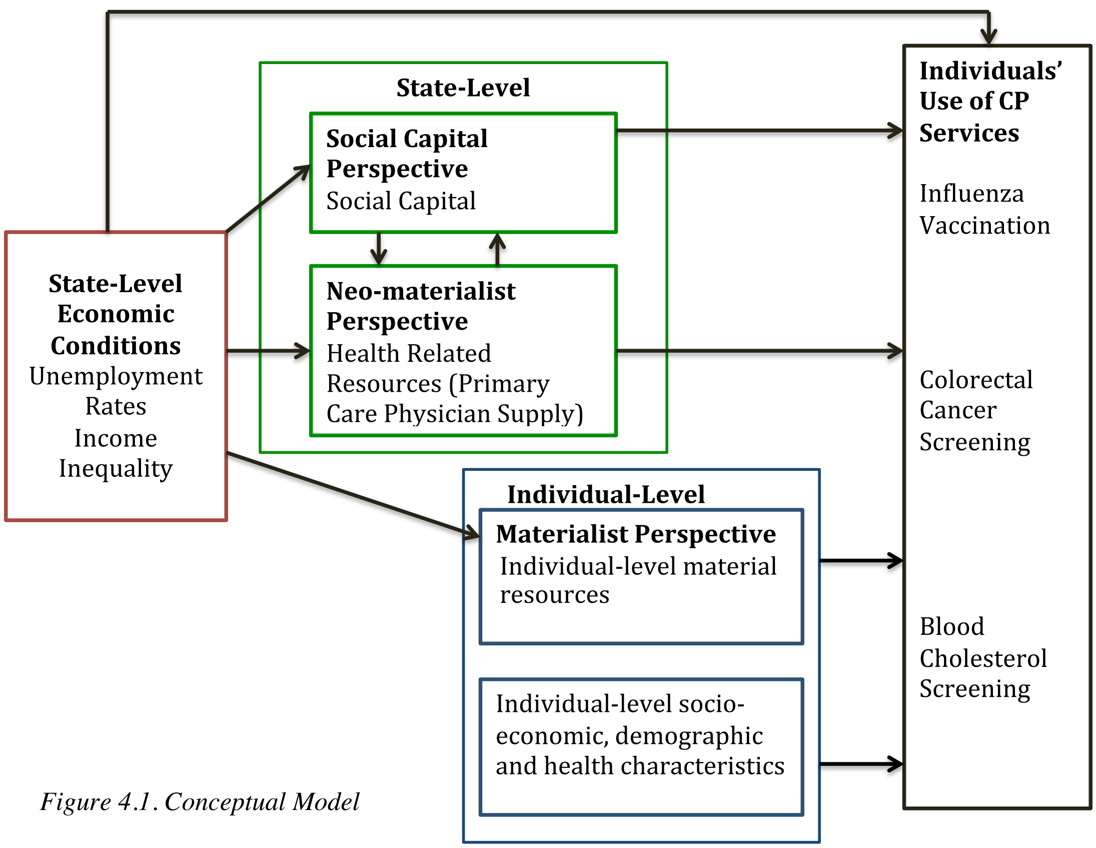

Figure 4.1. Conceptual Model

The model shows the relationship between economic conditions and CP service use. It also highlights the role of intervening factors, specifically social capital and health related resources, on individuals' use of CP services. Further, the model shows that social capital can affect the availability of health related resources, and vice-versa. Additionally, the model incorporates the materialist perspective whereby individual-level material resources shape the use of CP services. Finally, the model also acknowledges the contribution of individual-level socio-demographic, economic, and health related factors.

Research Questions

Broadly, the following research questions will be used to guide the study:

- Is there sufficient variation at the state-level to warrant multilevel modeling for each of the CP services examined?
- How do state-level unemployment rates affect individuals' use of CP services?
- How does state-level income inequality affect individuals' use of CP services?
- Does the effect of state-level unemployment and income inequality on individuals' use of CP services remain after controlling for individual-level material resources?
- Does the impact of state-level economic conditions on individuals' use of CP service use vary by income groups?
- How does state-level social capital affect individuals' use of CP services after taking into account other contextual and individual-level factors?
- How does availability of area-level health related resources, specifically state-level primary care physician supply, affect individuals' use of CP services after taking into account other contextual and individual-level factors?

Specific Aims and Hypotheses

The relationship between economic and social conditions, and CP service use is guided by the literature reviewed in Chapters 2, 3, and 4. The following specific aims have been developed for the study:

Specific Aim 1: Examine the relationship between state-level economic conditions and individuals' use of CP service use.

Specific Aim 2: Examine the relationship between state-level social capital and individuals' use of CP services

Specific Aim 3: Examine the relationship between state-level health related resources, specifically availability of primary care physicians, and individuals' use of CP services.

Specific Aim 4: Determine whether the effect of state-level income inequality on individuals' use of CP services varies by income levels.

While the conceptual model provides an overall snapshot of the relationships between the key independent and dependent variables, it is important to note that some of these relationships may differ based on the CP service outcome examined. It is entirely possible, for example, that the relationships between state-level factors and individuals' use of CP services varies due to differences in accessibility, safety, and risk associated with each CP service. Thus, based on the differences between the CP services and the existing literature presented in Chapters 2, 3, and 4, the following hypotheses have been developed.

Specific Aim One

For Aim one, the direction of the relationship between unemployment rates and CP service use is unclear, and existing research has found evidence in both directions. For example, as noted by Ruhm (2000), it is possible that individuals make healthier decisions when unemployment rates are high because they have more leisure time and/or because the opportunity cost of time declines. On the other hand, it is also possible that individuals forego or delay health related behaviors because they are distracted by the threat of unemployment (Catalano et al., 2003). Moreover, the relationship between unemployment and CP service use may differ based on the accessibility, safety, and risk associated with each CP service use. For example, it may be that unemployment rates exert negative effects on individuals' use of influenza vaccinations and blood cholesterol screening, but positive effects on individuals' use of endoscopic colorectal cancer screening due to the differences in accessibility, safety, risk, and time requirements. For income inequality, there appears to be a consensus in the current literature regarding the direction of the relationship. Generally, income inequality reduces health and propensity to engage in health related behaviors. Thus, the following hypotheses have been developed.

- $H_{1\text{-}1}$: High state-level unemployment rates will have a significant negative effect on individuals' use of influenza vaccination and blood cholesterol screening, net of individual-level characteristics.
- $H_{1\text{-}2}$: High state-level unemployment rates will have a significant positive effect on individuals' use of endoscopic colorectal cancer screening, net of individual-level characteristics.
- $H_{1\text{-}3}$: Individuals residing in states with high-income inequality will be less likely to use influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screenings, after controlling for individual-level characteristics.

Specific Aim Two

The relationships between social capital and health appear to work through multiple mechanisms. The majority of studies find a positive relationship between elements of social capital and CP service use. The following hypotheses have been developed to address the second specific aim.

- $H_{2\text{-}1}$: Individuals residing in areas with higher associational involvement, confidence in the medical institution, confidence in the media, and social trust will be more likely to use influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screenings.

Specific Aim Three

The existing research suggests that availability of healthcare resources may facilitate health utilization and encourage use of CP services. This may be due to direct mechanisms that improve access to care. Alternatively, it may be due to richer social networks between physicians that encourage sharing of information and resources. This latter mechanism may be especially salient for CP services that are not directly performed by primary care physicians. The following hypothesis has been developed.

- $H_{3\text{-}1}$: Individuals residing in areas with greater primary care physician supply will be more likely to use influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screenings.

Specific Aim Four

The last aim investigates whether the effect of income inequality on individuals' use of CP service use varies by income groups. There is evidence to suggest that high-income inequality adversely affects health, even among individuals with high incomes (Wilkinson and Pickett, 2011). However, there is also evidence that suggests those in the lower income groups are particularly vulnerable to the effects of high-income inequality (Kawachi et al., 2008). This may also depend on the cost of the CP service. For example, blood cholesterol screening is widely available and relatively inexpensive. Similarly, influenza vaccinations are relatively inexpensive, especially compared to colorectal cancer screening. Given these considerations, the following hypotheses have been developed.

- $H_{4\text{-}1}$: Low-income individuals residing in areas with high-income inequality will have lower likelihood of influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screenings.

Summary

In this chapter, I outline the gaps in the current literature. I also provide a conceptual model to guide the current study. I offer four specific aims for the current study: 1) Examine the relationships between state-level economic conditions and individuals' use of CP services; 2) Examine the relationship between state-level social capital and individuals' use of CP services; 3) Examine the relationship between state-level health related resources, specifically primary care physician supply, and individuals' use of CP services; and, 4) Determine whether the relationships between economic conditions, social conditions, and individuals' use of CP services differs by income groups.

Chapter Six: Data and Methods

This chapter is organized into two sections. In the first section, I provide a brief overview of the conceptualization and measurement of the key state-level independent variables, economic conditions, social capital, and health related resources, as well as a description of the corresponding data sources and measures. I then provide a detailed description of all individual-level variables, including description of the data sources, dependent variables, and control variables. The second section explains how the final dataset is constructed and provides a detailed description of the analytical methods used.

Contextual-Level Data and Measures (Independent Variables)

There are several key state-level factors examined in the current study, economic conditions, social capital, and primary care physician supply. In the following section, I provide a brief overview of the conceptualization and measurement of each of these constructs.

Economic Conditions

There are multiple ways of conceptualizing economic conditions to capture the state of the economy in a given area. Historically, two distinct measures are often used, unemployment and income inequality (BLS, 2014). Collectively, these measures provide important information on joblessness and income distribution (Kawachi, 2000; Roberts, Povich, & Mather, 2013; Bureau of Labor Statistics, 2014). Unemployment data is obtained from the Bureau of Labor Statistics (BLS) and income inequality data is obtained from Mark W. Frank's Income Inequality dataset (2008).

Unemployment data and measures. The BLS (2014) is the regulatory agency responsible for computing the national unemployment rate as well as unemployment rates for all states and territories in the United States. The unemployment rate captures the number of unemployed persons in the labor force, and is a key measure of economic conditions. According to the BLS (2014), the measure is designed to capture "a person who is actively searching for employment but is unable to find work" (BLS, 2014). Data is derived from the Current Population Survey (CPS), a nationally representative sample of households in the United States that collects detailed information on participants' employment status. National and state-level unemployment rates are computed (BLS, 2014) by dividing the total number of unemployed individuals by the total number of people in the labor force (BLS, 2014). Thus, the unemployment rate is a measure of joblessness in the country, and is also an important indicator of economic growth and job security in a given area (BLS, 2014).

Despite the widespread use of the unemployment rate as a key measure of economic conditions, there are nonetheless a number of limitations associated with the measure. First, the unemployment rate may lag behind current economic conditions (Blodget, 2009). As a result, during major economic shifts, the contemporaneous unemployment rate is unable to capture changes instantaneously, and there is a period of time when the unemployment rate does not reflect the current economic state. Another concern with the unemployment rate is that it does not take into account individuals who have become frustrated with seeking a job (BLS, 2014). These "discouraged workers" are not included in unemployment rate calculations (BLS, 2014). Thus, the unemployment rate may actually underestimate the degree of unemployment in a given area. Additionally, the unemployment rate does not take into account individuals who may be working, but are underemployed (BLS, 2014). If this is the case, it means that the official unemployment rate may not accurately reflect the economic conditions in an area. The unemployment rate also does not capture changes in earnings (BLS, 2014). For example, if individuals take pay cuts to retain jobs, they are still employed so this aspect is not included in unemployment rate calculations. Consequently, it is possible for states to have similar unemployment rates, but very different economic profiles.

Despite these concerns, the unemployment rate provides an overall snapshot of unemployment in the country and possesses considerable advantages. First, it is the main measure of joblessness in the country. Second, it is computed consistently across states. In the current study, I use unemployment rate data from the BLS. Consistent with previous research (Tefft & Kageleiry, 2013; Ruhm, 2000), I use a one year lagged unemployment measure. That is, if the individual-level dependent variable is collected in 2011, I use unemployment rates from 2010. For interpretation purposes, I standardize the unemployment rate by subtracting the overall mean and dividing by the standard deviation.

Income inequality data and measures. Income inequality is another important measure of an economy's health. It captures the distribution of income in a given area (Wilkinson & Pickett, 2011). While there are different methods of calculating income inequality, at its core, it refers to determining the concentration of income among different segments of population (Wilkinson, 1992; Wikinson & Pickett, 2011). Thus, the various income inequality measures capture differences in the distribution of material resources between individuals and/or households (Wilkinson, 1992; Wilkinson & Pickett, 2011). In so doing, these measures capture the gap between individuals and households that make the most of the income in a delineated area and those that make the least. Because of this feature, income inequality measures are also thought of as measures of relative poverty.

The most commonly used measure of income inequality is the Gini Coefficient, also known as the Gini Index. The Gini Index is computed by first calculating a Lorenz curve, a graphical representation of income distribution where the horizontal axis represents the cumulative percentage of income distribution from smallest to largest and the vertical axis represents the percent of total income in the economy (Lorenz, 1905). The Lorenz curve plots these percentages (Farris, 2010)). A society characterized by perfect equality appears as a 45° straight line where the bottom quarter of the population possesses a quarter of the total income (Farris, 2010). Societies that are unequal have Lorenz curves that are farther away from the straight line of equality (Farris, 2010). The Gini Index is then calculated from this curve (De Maio, 2007). Higher values of the Gini Index indicate higher levels of inequality (De Maio, 2007).

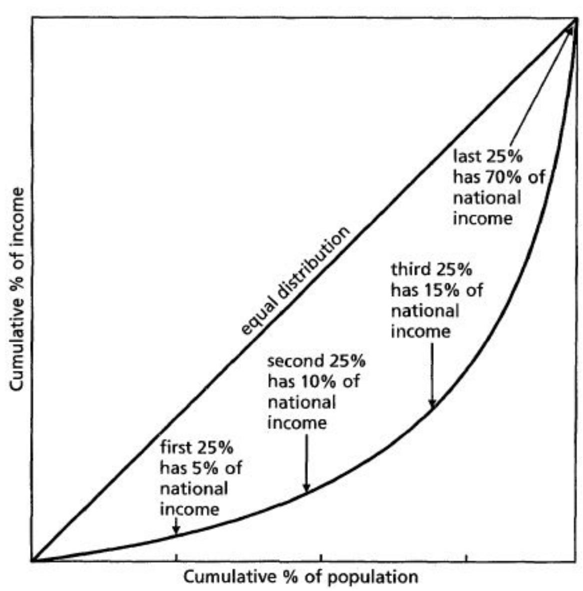

Figure 6.1. Lorenz Curve to Calculate the Gini Index.
Obtained from: Oxford Dictionary of Geography (Mayhew, 2004).

Even though the Gini Index is a commonly employed measure of inequality, there are some limitations associated with the measure. Namely, the Gini index captures the overall inequality in a given area, but it is insensitive to where income transfers occur (De Maio, 2007). That is, if income is transferred between two wealthy individuals, such a transfer affects the curve in much the same way as income transferred between two poor individuals (World Bank, 2011). De Maio (2007) highlights this problem in his work, noting that a major limitation of the measure is its inability to differentiate between the various types of inequalities that may occur.

Other approaches to calculating income inequality include measures to capture the top 10% or top 1% of income shares. These measures capture the income share of the largest top 10% or top 1% of individuals (World Bank, 2011). The more income shares these groups possesses, the greater the inequality in income distribution.

In the current study, I use the Gini Index to measure income inequality. This measure is available from Mark W. Frank's (2008) Income Inequality Dataset. This dataset presents a considerable advantage over other measures of income inequality because it is based on data obtained from the Internal Revenue Service (IRS). Often, income inequality measures are constructed from Census Data, using gross income that is not adjusted for household size, subsidies, and other income transfers (Kawachi, 2000). However, Frank (2008) addresses the limitations by constructing the Gini Index using tax data reported in the *Statistics of Income Bulletin (SOI)*, a quarterly bulletin that contains detailed information on filed tax returns. Thus, income inequality measures are constructed based on pretax adjusted gross income using information about individuals' wages, salaries, capital income, and entrepreneurial income.[7]

The Gini Index is measured on a 0-1 scale, with 0 representing perfect equality and 1 representing perfect inequality. To ease interpretation, I standardize this variable by subtracting the overall mean and dividing by the standard deviation. The mechanisms through which income inequality affects health and health related behaviors do not occur contemporaneously with income inequality, but rather accrue incrementally over time (Gadalla & Fuller-Thompson, 2008). Existing research suggests that there is a five to fifteen year lag before income inequality affects health (Blakely et al., 2000; Gadalla & Fuller-Thompson, 2008). Therefore, in the current study, I use a ten-year lag for income inequality.

Social Capital Data and Measures

Social capital is a difficult concept to operationalize because of its multidimensional nature. There are many definitions and perspectives on social capital, and the concept has been measured in a number of different ways, depending on the topic of inquiry.

Bourdieu (1977), Coleman (1988), and Putnam (1995; 2001) are widely accepted as the "founding fathers" of social capital and they offer three distinct but overlapping

[7] The income inequality measure is constructed based on pretax adjusted gross income. Capital income consists of dividends, interest, as well as rents. Entrepreneurial payments consist of income from self-employment, small business, and other business arrangements. The data does not include interest on state and local bonds or transfers of income from federal and state governments. Complete details can be found on Mark W. Frank's (2008) webpage on income inequality.

perspectives on social capital. Bourdieu offers arguably the most theoretically sophisticated conceptualization of social capital, defining it as "the sum of the resources, actual or virtual, that accrue to an individual or group by virtue of possession of a durable network of more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu & Wacquant, 1992, Pg. 119). Thus, social capital accrues to individuals and groups through social networks.

Coleman (1998; 1990) provides a more functional perspective of social capital, explaining that the interaction between rationality, social norms, and social structures give rise to social capital. Thus, social capital is a resource that inheres in social structures and facilitates action (Coleman, 1998; 1990).

Putnam (2001), credited for bringing social capital to the mainstream, approaches social capital from a political science perspective by identifying civic and political participation as elements that also engender social capital. Operating within social networks and group memberships, participation in society (e.g. involvement with groups) nurtures reciprocity, trust, coordination, and communication within a community (Putnam, 2001). Social capital is generated through this process and is a resource for cooperation, democracy, and social relations in a community. It is examined by collecting information on voter turnout, newspaper readership, membership in associations, feelings of trust, and levels of honesty (Putnam, 2001).

Given the broad-ranging perspectives on social capital, it is not surprising that there are a variety of measures employed to measure social capital. Most common conceptualizations of social capital include dimensions of social networks, civic participation, and trust and confidence in institutions (Cote & Healy, 2001; Foxton &

Jones, 2011). Social network measures aim to capture the quantity and quality of individuals' social interactions, in addition to general feelings about connections with others. Involvements in social networks generate and facilitate the flow of information and resources. Volunteering, participating in community services, or being a member of an association are all activities subsumed within civic participation (Foxton & Jones, 2011). Similar to social networks, civic participation facilitates the flow of information and resources and in so doing, generates social capital. Measures of civic participation include questions that assess the quantity and quality of involvement in associations and organizations such as neighborhood groups and bowling leagues (Foxton & Jones, 2011, Putnam, 2001).

Trust and confidence are also important components of social capital (Putnam, 2001). These concepts are particularly challenging to measure due to their multidimensional nature (Glaeser, Laibson, Scheinkman, & Soutter, 2000). Because trust and context are closely intertwined, trust varies from setting to setting. Questions to assess trust must be context specific to have meaning and relevance (Glaeser et al., 2000). For example, trust in family is viewed distinct from trust in government or other institutions. Similarly, confidence in political institutions is viewed distinct from confidence in other types of institutions (e.g. medical). Assessments of confidence are based on complex interactions between individuals' experiences, attitudes, and beliefs about specific institutions (Gidman, Ward, and McGregor, 2012; Gilson, 2003).

To further complicate matters, there is some disagreement about the role of trust in social capital. Some researchers (e.g. Putnam, 2001; Fukuyama, 1995) view trust as a key component of social capital. Others note that trust arises as a result of social capital

(Woolcock, 2001), that is, trust is a consequence of social capital. Still others posit that trust is necessary for the development of social capital; that is, trust is a prerequisite of social capital (Glaeser et al., 2000). Regardless of these differences, there is agreement that trust is intimately tied to social capital.

Generally, there are three types of trust examined in the social capital literature, interpersonal trust, social or generalized trust, and institutional trust. Questions designed to measure interpersonal trust assess the degree to which individuals accept vulnerability or risk based on existing expectations of others (Borum, 2010). Social trust questions aim to assess people's general feelings about their faith in others (Torche & Valenzuela, 2011). Institutional trust questions assess individuals' confidence in institutions such as the government, press, and medical institutions (Foxton & Jones, 2011).

Structural and Cognitive Dimensions of Social Capital

Although there are multiple ways of conceptualizing and measuring social capital, measures can be distinguished based on whether they capture structural or cognitive dimensions of social capital (Grootaert & Van Bastelaer, 2002). Structural social capital refers to what people do (e.g. involvement in associations and groups). Cognitive social capital refers to what people feel (e.g. trust in government), thus capturing a more subjective dimension of social capital (Grootaert & Van Bastelaer, 2002). The latter incorporates elements of trust (e.g. social trust and trust in institutions). Although these two aspects of social capital, structural and cognitive, are related, they are also different constructs and should be examined separately (Harpham et al., 2002).

Data Sources and Measures

State-level social capital measures are constructed using data from the General Social Survey.

General Social Survey (GSS). The GSS is a repeated biennial cross sectional face-to-face survey of approximately 1,200 to 2,500 English-speaking participants in the United States (NORC, 2013; Smith et al., 2013). The GSS is representative of the non-institutionalized U.S. adult population in the United States. According to NORC (2013), the GSS employs a full probability sampling of households. Under this sampling scheme, each household has an equal probability of selection within counties and metropolitan statistical areas in the United States. The survey first began in 1972 and was administered annually until 1993, when it switched to a biennial administration.

The GSS is the major source of information on Americans' political, social, and cultural attitudes (NORC, 2013; Smith et al., 2013). The survey consists of several types of questions, including a replicating core portion, and various supplemental modules (NORC, 2013; Smith et al., 2013). The GSS' replicating core questions are repeated questions that are asked at every administration of the GSS. These questions ask participants about their demographic and other background characteristics, as well as their social and political attitudes and behaviors. Some of these questions are asked to a random two-thirds of the sample due to time and budget constraints (NORC, 2013; Smith et al., 2013). Module questions are based on new and innovative issues and cover a range of topics. During the early years, survey administers relied on paper and pencil to administer the survey. Currently, administrators use computer assisted personal interviewing (CAPI), though telephone interviews are still used when necessary.

The GSS is particularly appropriate for the current study because it contains social capital measures that have been widely used in the literature (Galea, Karpati, & Kennedy, 2002; Kawachi et al., 1999; Mellor & Milyo, 2005). Specifically, the survey collects information on individuals' attitudes towards various institutions, including the government, medicine, and the press. It also collects information on participants' voluntary involvement in associations and organizations. Many studies use the dataset to derive state-level estimates of various social capital indicators (Galea et al., 2002; Kawachi et al., 1999; Mellor & Milyo, 2005)[8]

While the GSS possesses many advantages, there are nonetheless several limitations. First, although the dataset contains a number of questions designed to assess social capital, there are no measures available to capture the extent of individuals' involvement in groups and networks. Relatedly, existing questions do not assess the quality of social participation. The measures that are available are for a small subsample of participants and sample size limitations prevent aggregation to the state-level. Third, because the GSS is designed to provide nationally representative estimates, some states are not sampled every year. Thus, it is necessary to pool data over many years to increase sample size. Consequently, social capital estimates constructed using the GSS represent average state-level social capital estimates across years. While this is a limitation, social capital is fairly stable, and changes occur gradually over long periods of time (Lillbacka, 2006; Putnam, 2001). Despite these limitations, the GSS employs standard measures of social capital that are widely used in previous research.

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[8] Although state identifiers are not publicly available, they can be obtained from NORC.

Social capital measures. Broadly, social capital measures are constructed by obtaining the individual-level data from the GSS, applying post-stratification weights, and constructing state-level estimates for each indicator.

For all cognitive measures of social capital, I pool data across years from 1990 to 2010 for a total 30,194 participants. However, the GSS does not ask every question of all participants every year; in some years, some survey questions are administered to only two-thirds of the sample. After accounting for this design and missing data, the sample size varies for each social capital indicator.

I use three measures of trust and confidence: social trust, confidence in medical institution, and confidence in the press.

Social trust is measured by a question asking participants, “Generally speaking, would you say that most people can be trusted or that you can’t be too careful in dealing with people.” Participants are provided the following response options: “can trust,” “cannot trust,” and “depends”. These responses are coded as 0 if participants report “cannot trust,” 1 if they report, “depends,” and 2 if they report, “can trust.” There are 19,549 participants who answer the social trust question, with an average of 399 participants for each state.

Confidence in Medicine is measured by asking respondents: “I am going to name some institutions in this country. As far as the people running these institutions are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them?” Respondents are then asked to provide their response for several institutions, including medicine. Three response options are available, “a great deal,” “only some,” and “hardly any.” Responses are coded so that 0 refers to individuals with "hardly any" confidence, 1 refers to individuals with "only some" confidence, and 2 refers to individuals with "a great deal of confidence." There are 17,026 participants who answer the confidence in medicine question, with an average of 347 for each state.

Confidence in the media is a composite measure based on participants' responses to two questions: whether they have confidence in the press and whether they have confidence in television. Specifically, confidence in the media is measured with the following: "I am going to name some institutions in this country. As far as the people running these institutions are concerned, would you say you have a great deal of confidence, only some confidence, or hardly any confidence at all in them?" Respondents are then asked to provide their response for several institutions, including the press and television. Three response options are available for each question: "a great deal," "only some," and "hardly any." Responses are coded so that 0 refers to individuals with "hardly any" confidence, 1 refers to individuals with "only some" confidence, and 2 refers to individuals with "a great deal of confidence." Based on these questions, I construct a single composite measure that captures respondents' confidence in the media. Responses for this item range from 0 to 4. There are 16,868 participants who answer both the confidence in the press and confidence in the media questions, with an average of 344 participants for each state.

Constructing state-level measures of social capital. To construct state-level estimates of social capital, I develop and apply post-stratification weights before estimating state-level measures for each indicator.

The GSS is not representative at the state-level so post-stratification weights are necessary. Post-stratification weights are widely used in sociology and political science to adjust sample to population totals for each state. To do this, I follow the procedure outlined by Kawachi et al., (1997) and Kawachi and colleagues (1999) and employed by Mellor & Milyo (2005), Galea and colleagues (2002) and others. Specifically, I construct post-stratification weights by examining the age, race, and educational attainment distributions of participants in the GSS. As outlined by Kawachi and colleagues (1997), weights can be calculated according to the following formula:

$$W_{ijkl}=P_{ijkl}/p_{ijkl} ,$$

W_{ijkl} is the post-stratification weight for the GSS respondent in the *i*th state, in the *j*th age group, the *k*th race and the *l*th level of educational attainment. The weights are constructed by dividing the proportion of individuals with the same characteristics in the U.S. population (based on the 1% Public Use Microdata Sample from the U.S. Census) by the corresponding proportion of participants in the GSS.

I estimate state-level social capital for each social capital indicator outlined above[9]. Broadly, I group states into three categories, high, medium, or low based on the mean and standard deviation of each social capital indicator across states. States with mean averages one standard deviation below the average are grouped as low. States with mean averages one standard deviation above the average are grouped as high. States in between are grouped as medium.

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[9] Associational involvement is retained as a continuous variable.

Neo-Material Perspective: Area-Level Resources

There are many different types of area-level resources used to examine the neo-material perspective. Studies that examine the relationship between area-level resources and health have commonly employed health related measures such as number of hospital beds, physician supply, quality of air and water, housing, affordable and nutritious food availability and the presence of health and welfare services, to name a few (Alexander et al., 1999; Safford & Marmot, 2003). In the current study, I use one main measure as a proxy for area-level health related resources, primary care physician supply. This data is obtained from the Association of American Medical Colleges (AAMC, 2011) 2011 State Physician Workforce Data Book. I also use an additional measure of a state's participation in the Colorectal Cancer Control Program (CRCCP) as a specific area-level health related resource when examining colorectal cancer (CDC, 2013c). This program provides resources to some states to improve screening rates for colorectal cancer (CDC, 2013c).

Primary Care Physician Supply (2011)

The 2011 State Physician Workforce Data Book constructs state-level estimates of physician supply using data from the American Medical Association's (AMA) Physician Masterfile (AAMC, 2011; AMA, 2014). The AMA's Physician Masterfile compiles extensive information on over 1.4 million physicians and medical students in various stages of their careers (AMA, 2014). This data provides details on the current physician supply, medical school enrollment, and medical education in the United States (AMA, 2014). Data is collected from a variety of sources including, physicians' surveys, medical school surveys, and state licensing boards (AMA, 2014). Data is available for each state and the District of Columbia. The 2011 State Physician Workforce Data Book uses this information to construct physician supply at national and state-levels (AAMC, 2011).

Despite the advantages of this data, there are several limitations. First, the data is based on self-reports of physicians' primary and secondary specializations so the possibility of self-report bias exists. Second, the AMA (2014) Physician's Masterfile is is unable to keep track of all workforce related changes. For example, if physicians change their specialty area, pass away, or retire, these changes are not immediately reflected in the data because physician surveys are administered periodically (AMA, 2014).

Despite these limitations, this data presents an important opportunity to examine how primary care physician supply shapes individuals' use of CP services. In the current study, I use a measure of active primary care physician supply that is available in the 2011 State Physician Workforce Data Book (AAMC, 2011). Active primary care physicians are physicians that currently practice medicine in the areas of adolescent medicine, family medicine, general practice, geriatric medicine, internal medicine, internal medicine/pediatrics, or pediatrics (AMA, 2014; AAMC, 2011). Population estimates from the U.S. Census are used to construct per capita estimates for each state (AAMC, 2011).

CDC's Colorectal Cancer Control Program (CRCCP)

This CDC's CRCCP program was initiated in 2009 and provides funding to some states and tribal organizations in the United States to increase use of colorectal cancer screening among low-income men and women between the ages of 50 and 75 years

(CDC, 2013c). This program represents an area-level health related resource that specifically targets low-income areas and underserved populations. Program components include educating communities about colorectal cancer and the available screening options, pooling the existing health related resources to serve low-income populations, and offering colorectal cancer screening to underserved populations (CDC, 2013c).

While the CRCCP program is an important measure of a targeted health related strategy to address shortages in screening among low-income communities, this measure does not capture the amount of funding available to each state participating in the program and/or the intervention strategy employed. Thus, it is possible that there are differences between states in funding amount and the type of health promotion strategy used to educate individuals on the importance of colorectal cancer screening.

Despite these limitations, this information presents an opportunity to examine how targeted state-level strategies shape individuals' use of CP services. In the current study, I create a dichotomous indicator of each state and territories' participation in the CRCCP program. Responses are coded as 1 if a state receives funding for the program and 0 otherwise.

Individual-Level Data and Measures

All individual-level data is obtained from the 2010 and 2011 Behavioral Risk Factor Surveillance System (BRFSS).

Behavioral Risk Factor Surveillance System (BRFSS)

The BRFSS is an annual state-based cross-sectional telephone survey of non-institutionalized adults in the United States. The survey is a joint effort between the Centers for Disease Control and Prevention (CDC), state health departments, and some universities (CDC, 2013a; CDC, 2013b). Since its inception in 1984 when fifteen states participated, the survey has expanded to include all states and territories in the U.S (CDC, 2013a; CDC, 2013b). The BRFSS is particularly appropriate for this study because it collects detailed information on individuals' health behaviors, health related risk behaviors, CP service use, and health outcomes

Currently, the BRFSS questionnaire consists of four main components, core questions, optional CDC modules, and state-added questions (CDC, 2013a; CDC, 2013b). They are two types of core questions, fixed and rotating (CDC, 2013a; CDC, 2013b). Fixed core questions are asked by every state. Rotating core questions are asked every other year. The core questions allow for comparisons across states. The CDC (2013a; CDC, 2013b) also develops optional modules that consist of a set of questions on specific health topics. States may choose to incorporate the optional modules, if they desire. Additionally, states have the option to include other relevant questions as necessary. When it is necessary, the CDC includes questions on emerging health topics using the optional modules. The survey is administered through Computer Assisted Telephone Interviewing (CAPI) (CDC, 2013a; CDC, 2013b).

The BRFSS relies on disproportionate stratified sampling at the state-level to select participants (CDC, 2013b). Specifically, the Waksberg method is used in the majority of states to select participants[10]. The Waksberg method differs from random digit dialing because it adjusts for the probability of obtaining working household

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[10] Sampling in most states is based on the Waksberg method. Information obtained from previous surveys is used to classify 100-number blocks of telephone numbers into two groups that are either likely or unlikely to produce residential numbers. Telephone numbers in the group more likely to produce working household numbers have higher sampling rates.

telephone numbers (Montaquila, 2008). Specifically, telephone numbers are separated into 100-number blocks based on the likelihood of producing a working residential number (Montaquila, 2008; CDC, 2013b). Telephone numbers in blocks that are more likely to contain residential phone numbers are sampled at higher rates than the corresponding block of numbers that are less likely to produce working residential numbers. Participants are then selected randomly from among the adult members of a household. In 2011, the BRFSS began to include a small sample from cell phone only households, as well[11]. On average, the BRFSS administers the survey to more than 400,000 participants every year (CDC, 2013a; CDC, 2013b). In 2011, there were over 500,000 participants interviewed across the United States and the District of Columbia. In 2010, there were over 450,000 participants interviewed across the United States and the District of Columbia. Due to the sampling design, the average age of the sample is older, with a mean of 55 years of age for 2011 participants and 57 years of age for 2010 participants.

The BRFSS is particularly appropriate for this study because the survey collects detailed information on individuals' health, health related risk behaviors, major health events, chronic health conditions, and preventive services use (CDC, 2013a; CDC, 2013b). Specifically, the survey includes basic demographic and socioeconomic questions, including questions on health care coverage, and a variety of health utilization behaviors, including use of CP services. Additionally, state health departments use BRFSS data to construct state-specific estimates of preventive health practices and risky

[11] This was done to account for the increasing rates of cell-phone only households in the United States. In 2012, the percentage of cell-phone only households was estimated to be 35.8% (FCC, 2014).

behaviors so sample sizes at the state-level are large. Importantly, the BRFSS provides state identifiers for each respondent, thus providing a way to link external state-level data to individual-level BRFSS data.

Despite these advantages, there are a number of limitations associated with the BRFSS. The main limitation of the BRFSS is that it is based on self-reported data. Self reported data is vulnerable to a number of errors due to recall bias (Bernard, 2012). For example, existing research suggests that individuals sometimes assume they have received blood cholesterol screening tests if their doctor has ordered lab work (Goldman et al., 2006). Although blood cholesterol screening is often included as part of standard lab work, this is not always the case, so patients may misreport their blood cholesterol screening status. While clinical data on use of CP service would be ideal, this information is not available. Another limitation is that the BRFSS is administered in English and Spanish so adults who do not speak these languages are excluded from the sample (CDC, 2013a; CDC, 2013b). Additionally, until 2010, individuals who did not have a landline were excluded from the sampling strategy. In 2011, the BRFSS began to include a small percentage of cell phones in the sampling frame (CDC, 2013a; CDC, 2013b). Finally, BRFSS data collection is handled largely on a state-level. Although there is collaboration between the CDC and state health departments in designing the survey, data is collected at the the state-level. Thus, it is possible that there are differences in the quality of data across states (AHRQ, 2009; CDC, 2013a; CDC, 2013b).

In spite of these concerns, the BRSS provides detailed information of individuals' use of CP services at the state-level and presents an opportunity to better understand the contextual state-level correlates of CP service use. In the current study, I examine three

CP services, influenza vaccinations, blood cholesterol screening, and endoscopic colorectal cancer screening[12]. The 2011 BRFSS is used to examine the economic and social factors associated with influenza vaccinations and blood cholesterol screening. Questions on colorectal cancer screening are part of the rotating core. Participants are not asked if they have received these services in the 2011 BRFSS. Thus, the 2010 BRSS is used to examine the state-level economic and social factors associated with endoscopic colorectal cancer screening. For the purposes of the current study, the sample for each outcome is constructed based on the specific recommendations for each CP service as outlined in Chapter 2 and delineated in Figure A1 in Appendix B.

Influenza Vaccinations. According to the USPSTF (2013), influenza vaccinations are recommended annually for all adults. Thus, influenza vaccination status is constructed by asking respondents whether they have received a flu shot or a flu spray in the past 12 months. Responses are coded as 1 if participants report receiving either a flu shot or a flu spray, and zero if otherwise. The total sample consists of 438,133 participants.

Blood Cholesterol Screening. According to the AHA (2014), blood cholesterol screening is recommended for all individuals over the age of 20 at least once every five years. Blood cholesterol screening is assessed by two questions in the BRFSS that asks respondents whether they have ever received a blood cholesterol screening and if so, how long ago they received it. The responses are coded as 1 if participants report receiving blood cholesterol screening in the past five years and 0 if otherwise. After taking into account current recommendations, the sample consists of 453,170 participants.

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[12] In separate research, I also extend the analysis to additional CP service outcomes; these findings are in progress.

Endoscopic Colorectal Cancer Screening. Endoscopic colorectal cancer screening exams, particularly colonoscopies, are the gold standard for colorectal cancer screening, and are recommended for all adults between the ages of 50 and 75 (USPSTF, 2013b). Screening intervals are once at least every ten years for a colonoscopy and once every five years for a sigmoidoscopy[13]. To assess use of endoscopic colorectal cancer screening exams, I construct a dichotomous indicator that captures whether or not individuals have obtained a colonosocopy or a sigmoidoscopy within the past ten years. Responses are coded as 1 if yes and 0, otherwise. This question is constructed using two questions in the BRFSS: 1) "Have you ever received a colonoscopy or sigmoidoscopy?" And, 2) "How long ago was your last colonoscopy or sigmoidoscopy?" The total sample consists of 217,934 participants.

Control Variables. Based on Grossman's (1972) model of healthcare demand and Andersen's (1995) behavioral health model, I incorporate a set of human capital and health related variables in the model. These control variables account for the various demographic, socioeconomic, and health related traits that may influence use of CP services. Specifically, I control for individual-level age, gender, ethnicity, educational attainment, employment status, income levels, marital status, health insurance, and health status.

Dataset Construction

The final dataset was constructed using all the above-mentioned economic and social state-level measures and the individual-level data from the BRFSS. Specifically,

[13] The Fetal Occult Blood Test (FOBT) is recommended every year. This test is not included in the current study.

state-level economic and social data were linked with the individual-level BRFSS data using the Federal Information Processing Standards (FIPS) codes. There are 48 states and the District of Columbia included in the sample. This procedure was conducted for the 2010 BRFSS to examine colorectal cancer screening use and the 2011 BRFSS to examine influenza vaccination and blood cholesterol screening use.

Empirical Methods

I use multilevel modeling to examine how state-level economic and social conditions affect individuals' use of CP services (Bartels, 2008). Multilevel models consist of several types of mixed model approaches, including random intercept models, random slope models, and random intercepts and slopes model (Raudenbush & Bryk, 2002; Bartels, 2008). In the sociological literature, they are often referred to as hierarchical linear models (HLM), a term that highlights the nested structure of the data, where individuals are nested within higher units (Raudenbush & Bryk, 2002). Multilevel models can be used for data with several levels (e.g. students nested in classrooms, which are nested within schools), cross-classified data (i.e. when lower level units can be assigned into one or more higher level units), and different study designs (e.g. cross-sectional or longitudinal with repeated measures) (Bartels, 2008; Raudenbush & Bryk, 2002).

Multilevel model are appropriate for the current study for a number of reasons. First, implicit in this approach is the recognition that individual-level behavior occurs within a social context. Consequently, multilevel model estimation provides a measure of how much variance is attributable to the group level (Cheah, 2009; Bartels, 2008; Raudenbush & Byrk, 2002). Second, nested data violates the independent random sample assumption of ordinary least squares (Raudenbush & Byrk, 2002). Individuals within each group are not independent observations. Multilevel models correct standard errors and produce appropriate confidence intervals and significance tests. Additionally, multilevel models produce more precise parameter estimates (Bartels, 2008). Multilevel models separate the error term into two parts, within groups (level 1) and between groups (level 2) and allow the intercepts and/or coefficients to vary across groups. Moreover, multilevel models are one of the few techniques available that allow researchers to model both individual- and contextual-level factors to predict individual-level outcomes (Bartels, 2008).

Multilevel models estimate coefficients using a blend of variance component models and ordinary least squares techniques. Broadly, this is a partial pooling approach where the total variance in the dependent variable is partitioned into between and within group variance (Bartels, 2008; Raudenbush & Byrk, 2002). The intraclass correlation (ICC) (rho) is computed based on the total, within, and between group variance. A high ICC indicates that the amount of shared variance within groups is high; a low ICC indicates otherwise. Coefficient estimates are adjusted using a pooling factor that is derived from the ICC. By doing this, multilevel models adjust for correlated errors within groups and produce more precise coefficient estimates than standard regression techniques (Raudenbush & Byrk, 2002).

While multilevel models are the method of choice in the social sciences to examine nested data, there are some limitations and concerns associated with this method. First, this modeling strategy requires that independent variables must be uncorrelated with the error structure of the model and level-one independent variables must be uncorrelated with the level two residuals (Raudenbush and Bryk, 2002). If these assumptions are not met, coefficient estimates may be biased. Second, data limitations often prevent researchers from using multilevel models. Since the model relies on both within and between group effects, the number of groups and sample sizes within groups must be sufficient (Raudenbush and Bryk, 2002). While there is little consensus on what constitutes an appropriate sample size within clusters, existing studies suggest that there should be at least 30 clusters and at least 50 individuals nested within clusters (Maas and Hox, 2004, 2005). In the current study, there are 49 groups and sample sizes of over 50 individuals within each group.

In the current study, I use multilevel models to examine the relationship between contextual-level factors and individuals' use of CP services, while controlling for individual-level factors. Multilevel models are suitable for this study because they allow for an estimation of the following: the effect of state-level contextual factors on individuals' use of CP services, the effect of individual-level factors on individuals' use of CP services, and the effect of state-level contextual factors on individuals' use of CP services, after controlling for individual-level characteristics.

Model Construction

There are multiple ways of constructing multilevel models (Bell, et al., 2013). Raudenbush and Bryk (2002) provide some tips on how to do so. To begin, they recommend estimating an initial null model so that the variance can be partitioned between individuals and groups. This model is especially important because it provides information on the degree of ICC. It is important to note that the ICC may be small, particularly in cases where the group size is large (e.g. states). The appropriateness of using multilevel models rests on the ICC, the state-level variance, and likelihood ratio statistic test that compares the standard model with a multilevel model (Raudenbush and Bryk, 2002; Bartels, 2008). Accordingly, for each outcome examined, I first estimate an intercept only model. Additionally, I conduct the likelihood ratio test for all three CP service outcomes to determine if a multilevel modeling strategy is appropriate.

I estimate four distinct stacked model specifications for each CP service outcome examined based on specific groups of explanatory variables. I first estimate the effects of the main explanatory variables of interest, beginning with state-level economic conditions. Thus, Model A consists of only the state-level economic indicators, unemployment rate and the Gini index. This specification reveals whether there is any relationship between the state-level economic variables and each CP service outcome. It also allows for an examination of how much of the shared state-level variance is reduced from the null model after including the state-level economic variables. The second specification, Model B, includes all measures for the intervening state-level mechanisms, social capital and health related resources. This specification also allows for an examination of how much, if any, additional variance at the state-level is reduced after adding in these variables. The third specification, Model C, introduces the individual-level variables, a standard set of demographic and socioeconomic variables (e.g. age, race, ethnicity, education, employment status, income levels). These variables are consistent with Grossman's (1972) model of healthcare demand and are included as individual-level predisposing and enabling factors under Andersen's (1995) model of behavioral health. In the final model, lifestyle and health related variables are added to the model. Introducing the explanatory variables using a stacked model approach presents an opportunity to determine whether the individual-level sets of explanatory variables (demographic and socioeconomic, lifestyle and health) reduce the relationship between state-level factors and individuals' use of CP services.

Analytical Strategy

I use multilevel models to estimate how state-level and individual-level factors shape individuals' use of CP services. The fully specified equation can be written as:

$$\log\{p_{ij}/(1-p_{ij})] = y_{ij} = \beta_0 + \beta E_j + \beta I_j + \beta X_{ij} + u_j, \qquad (1)$$

where y_{ij} is the decision to obtain a CP service[14] for individual i in state j based on an unobserved latent variable y^*. In this specification, $y_{ij} = 1$ if $y^*_{ij}>0$, and 0 otherwise. β_0 is the intercept across states, E_j is is a vector of economic conditions for each state, I_j is a vector of social conditions for each state, X_{ij} is the vector of covariates for participant i in state j, and u_j is the state-level unobserved heterogeneity. Coefficient estimates are produced as log-odds. I use Stata 12.0 for all analyses (Stata Corp, 2011).

Following other studies, I use listwise deletion of missing data due to the presence of bias that occurs when multiple imputation methods are used in multilevel analyses (Petrin, 2006). Additionally, for model specifications A (economic conditions) and B (social conditions), I also estimate variance inflation factors to assess degree of multicollinearity between contextual-level variables.

[14] There are three separate multilevel models estimated, one for each of the three CP services examined, influenza vaccination, blood cholesterol screening, and endoscopic colorectal cancer screening.

Stratified Analyses

I also estimate models stratified by income. Stratified analysis based on income is conducted to determine whether the relationship between income inequality and individuals' use of CP services is more pronounced for individuals with lower incomes. If this is the case, it suggests that those in lower income groups are particularly vulnerable to the effects of income inequality. If this is not the case, it suggests that the effects of income inequality are uniform across income distributions, thus lending support to Wilkinson and Pickett's (2011) hypothesis that income inequality affects health for all individuals. This, of course, would suggest that there are larger mechanisms that occur as a result of state-level income inequality that trickle down to the individual-level to shape health behaviors.

Additionally, for influenza vaccinations and blood cholesterol screening, I also estimate models stratified by age, dividing the sample into working and non-working age groups[15]. Stratification based on working age and non-working age is conducted to determine whether the results are consistent across age groups. These results are presented in Appendix B. Additionally, for blood cholesterol screening, I also estimate models based on health, dividing the sample into good health and poor health. This is done to examine whether there are any differences by health status. It is possible, for example, that individuals in poor health are more likely to obtain blood cholesterol screening because it is part of chronic disease management, and not because it is a recommended CP service obtained as an investment in health. These results are presented in Appendix B.

[15] This is done because the BRFSS sample is older and software limitations prevent the use of weights in the multilevel analysis.

Summary

In this chapter, I outline the data sources, measures, and methods used for the current study. Specifically, state-level data is obtained from a variety of sources and individual-level data is obtained from the 2010 and the 2011 BRFSS. The main analytical method to examine how state-level economic and social conditions affect individuals' use of CP services is multilevel modeling. A stacked model approach is employed to construct models. Additional analysis is also conducted based on different income, age, and health groups.

Chapter Seven: Results

In the following section, I present results for all CP service outcomes examined in the current study, influenza vaccinations, blood cholesterol screening, and colorectal cancer screening.

Influenza Vaccinations

The total sample used to examine influenza vaccination status in the past year consists of 438,133 participants. Table 1A presents descriptive statistics for all variables used to model influenza vaccination. The information is reported for the full sample and by influenza vaccination status.

Descriptive Statistics

As can be seen from the table, approximately 46% (n=200,779) of participants report receiving the influenza vaccination in the past year. Individuals who report receiving influenza vaccinations tend to reside in states with lower income inequality and lower unemployment rates. Overall, about 19% of participants live in areas with low confidence in medical institutions, 69% live in areas with medium confidence in medical institutions, and 12% of participants live in areas with high confidence in medical institutions. Approximately 24% of individuals report residing in states with low confidence in the media, 62% report residing in states with medium confidence in the media, and 13% report residing in states with high confidence in the media. About 12% of participants live in states with low social trust, 56% report living in areas with medium social trust, and 31% reside in areas with high social trust. The per capita involvement in associations is 0.30 for the entire sample. There are an average of 93.82 total primary care physicians per 100,000 (population).

Individuals who report receiving an influenza vaccination in the past year tend to be older, female, and white. They have higher educational attainment, are more likely to not be in the labor market, and have higher household income. Moreover, they tend to be married, have fewer children in the household, and report having health insurance. Interestingly, individuals who report receiving the influenza vaccination in the past year tend to be those with lower health status. There are statistically significant differences between participants who report having received an influenza vaccination in the past year and those who do not.

Multilevel Model Results. I begin by estimating a variance component model (not shown), also known as an intercept only model, that partitions the variance between individuals and states. Because this is a multilevel logistic regression model, the level 1 variance is fixed at the variance of the standard logistic distribution ($\pi^2/3=3.29$). The level 2 (state-level) variance is 0.05 and is significant. The likelihood ratio statistic for testing the null hypothesis that the ICC is equal to zero is 4338.37, with a corresponding p value of less than 0.01. The intraclass correlation is 1.61%. Collectively, these statistics suggest that there is significant state-level variance and that the multilevel model is justified.

Table 1B presents the multilevel model results for influenza vaccinations. Models A and B include the contextual effects of state-level economic conditions and intervening factors, respectively. Interestingly, the addition of economic contextual factors reduces the state-level variance to 0.02. The addition of state-level social factors further reduces the state-level variance to 0.016. Models C adds the individual-level socio-demographic and economic variables and Model D, the final specification, adds individual-level lifestyle and health variables. In the final specification, estimates are conditional on individual-level socio-demographic, economic, lifestyle, and health variables.

Broadly, results indicate that individuals residing in areas with higher income inequality and higher unemployment rates have reduced odds of having had an influenza vaccination in the past twelve months. This relationship is consistent across all four-model specifications. In the final specification, Model D, which is conditional on state-level intervening mechanisms and individual-level socio-demographic, lifestyle, and health factors, a one standard deviation increase in income inequality reduces the odds (OR=0.954, $p<0.01$) of influenza vaccination by approximately 5%. Similarly, in Model D, a one standard deviation increase in state unemployment rate is associated with an approximately 8% reduction in an individuals' odds (OR=0.920, $p<0.01$) of receiving the influenza vaccination.

The intervening social mechanisms are added in Model B. Adding these contextual variables does not reduce the effects of income inequality or unemployment rate. The only social capital measure that is significantly associated with individuals' use of CP services is residing in a state with low confidence in the media, which reduces individuals' odds (OR=0.895) of having obtained the influenza vaccination in the past year by approximately ten percent.

Most of the individual-level variables affect influenza vaccination in the expected way and most are statistically significant. Among the individual-level factors, it appears that older individuals have greater odds (OR=1.026, $p<0.01$) of having obtained an influenza vaccination in the past twelve months. Individuals reporting their race as black have reduced odds (OR=0.765, $p<0.01$) of having obtained an influenza vaccination in the past twelve months relative to whites. Individuals reporting being Asian have greater odds ($OR=1.176$, $p<0.01$) of having obtained an influenza vaccination in the past twelve months. Individuals who report being Hispanic have greater odds ($OR=1.105$, $p<0.01$) of having obtained the influenza vaccination in the past twelve months relative to non-Hispanics.

There are significant differences in the effects of educational attainment on influenza vaccination. Specifically, individuals with high school degrees ($OR=1.071$; $p<0.01$), some college ($OR=1.204$, $p<0.01$), and college graduates ($OR=1.499$; $p<0.01$) have greater odds of having received the influenza vaccination in the past year relative to individuals with no high school degree. Individuals who report being employed also have greater odds ($OR=1.108$; $p<0.01$) of having received the influenza vaccination in the past year relative to those who are unemployed. Those who report not being in the labor market (i.e. students, home makers, retired, or otherwise unable to work) also report greater odds ($OR=1.393$, $p<0.01$) of having received an influenza vaccination in the past year relative to those who are unemployed.

As expected, individual-level income has a positive relationship with having received an influenza vaccination in the past year. Individuals who report having annual household incomes of $20,000 or greater have greater odds of having received the influenza vaccination in the past year across all income groups, relative to individuals who report household incomes of less than $20,000. In the final specification, individuals with annual household incomes of $20,000 to $35,000 have greater odds ($OR=1.086$, $p<0.01$) of having received the influenza vaccination in the past year. Those who report annual household incomes of $35,000 to less than $50,000 also have greater odds (OR=1.123, $p<0.01$) of having received an influenza vaccination in the past year. Individuals reporting annual household incomes of \$50,000 to less than \$75,000 report greater odds (OR=1.169, $p<0.01$) of having received the influenza vaccination in the past year. Individuals who report annual household incomes of \$75,000 or more also have greater odds (OR=1.336, $p<0.01$) of having received an influenza vaccination in the past year.

In terms of lifestyle and health characteristics, individuals who are married or living as married report higher odds (OR=1.042, $p<0.01$) of having received the influenza vaccination in the past year. Not surprisingly, individuals who have health insurance report over two times greater odds of having received the influenza vaccination in the past year (OR=2.292; $p<0.01$). Interestingly, those with better health status have lower odds of having received the influenza vaccination in the past year relative to those in poor health. Specifically, individuals who report having fair health status have reduced odds (OR=0.932; $p<0.01$), those who report good health status also have reduced odds (OR=0.813, $p<0.01$), those who report very good health status also have reduced odds (OR=0.740, $p<0.01$), and those who report excellent health status also have reduced odds (OR=0.644, $p<0.01$) of having received the influenza vaccination in the past year, relative to individuals who report having poor health status.

Stratified analysis. I also conduct stratified analysis by income. This is done to determine whether the effects of income inequality are more pronounced among those with lower income. To conduct this analyses, I examine two subgroups: individuals who report having an annual household income of under \$35,000 and those with household incomes of \$35,000 or greater. Results are substantively similar across both groups.

This suggests that the effects of income inequality and unemployment are uniform across income groups. Results for the age-based stratification are generally consistent with the main results and are presented in Tables A1A and A1B in Appendix B.

Blood Cholesterol Screening

The total sample used to examine blood cholesterol screening consists of 453,170 participants. The sample consists of only individuals who are 20 years of age or older. Table 2A presents descriptive statistics for all variables used to model influenza vaccination. The information is reported for the full sample and by blood cholesterol screening status.

Descriptive Statistics

Approximately 85% (n=386,268) of participants report having received blood cholesterol screening within the past five years. The average Gini Index is 57.04, with individuals who report receiving blood cholesterol screening residing in areas with higher income inequality than those who report no screening. The average unemployment rate is 8.86%, with individuals who report having received blood cholesterol screening residing in areas with higher unemployment rates. About 19% of participants live in areas with low confidence in medicine, 68% report living in areas with medium confidence, and 12% report living in areas with high confidence in medicine. Almost 24% of respondents live in areas with low confidence in the media, 63% live in areas with medium confidence in the media, and 13% live in areas with high confidence in the media. About 12% of participants live in areas with low social trust, 57% reside in areas with medium social trust, and 31% reside in areas with high social trust. The per capita involvement in associations is 0.30 for the entire sample. There are an average of 93.94 primary care physicians per 100,000 (population).

Individuals who report receiving blood cholesterol screening in the past five years tend to be older, female, and white. They have higher educational attainment, are more likely to be employed or not in the labor market, and report higher annual household income. Moreover, they tend to be married or living as married, have fewer children in the household, and are more likely to have health insurance. Interestingly, individuals who report having received blood cholesterol screening within the past five years tend to be those with lower health status. There are statistically significant differences between participants who report having received blood cholesterol screening within the past five years and those that report no screening.

Multilevel Models

I begin by estimating a variance component model, also known as the intercept only model, that partitions the variance between individuals and states. As noted earlier, because this is a multilevel logistic regression model, the level 1 variance is fixed at the variance of the standard logistic distribution ($\pi^2/3=3.29$). The level 2 (state-level) variance is 0.06 and is significant. The likelihood ratio statistic for testing the null hypothesis that the ICC is equal to zero is 3015.05, with a corresponding p value of less than 0.01. The intraclass correlation is 1.75%. Collectively, these statistics suggest that there is significant state-level variance and that the multilevel model is justified.

Table 2B presents the multi-level model results for blood cholesterol screening. Models A and B include the contextual level effects of economic conditions and social factors, respectively. Interestingly, the addition of economic contextual factors reduces the state-level variance to 0.054. The inclusion of state-level social factors further reduces the state-level variance to 0.029. Model C adds the individual-level socio-demographic and economic variables, and Model D, the final specification, includes individual-level lifestyle and health variables. In the final specification, estimates are conditional on individual-level socio-demographic, economic, lifestyle, and health variables.

Broadly, there are no significant effects of state-level income inequality on individuals' use of blood cholesterol screening. On the other hand, state-level unemployment has a statistically significant positive effect on individuals' use of blood cholesterol screening. The relationship is consistent across all model specifications. Specifically, in Model D, a one standard deviation increase in the state unemployment rate is associated with greater odds (1.088, $p<0.01$) of having obtained blood cholesterol screening in the past five years.

The social contextual variables are added in Model B. These variables do not reduce the effect of unemployment rates on blood cholesterol screening. The only social capital variable that is significantly associated with individuals' use of blood cholesterol screening is confidence in the media. Specifically, residing in a state with low confidence in the media reduces the odds (OR=0.835, $p<0.01$) of having had blood cholesterol screening in the past five years, relative to residing in a state with medium confidence in the media. Conversely, residing in a state with high confidence in the media is associated with greater odds (OR=1.185, $p<0.05$) of individuals' use of blood cholesterol screening in the past five years relative to residing in a state with medium confidence in the media. While total primary care physician supply is positively associated with individuals' use of blood cholesterol screening in Models B and C, this relationship is not significant in the final specification (Model D), after health related variables are included.

Most of the individual-level predictors affect blood cholesterol screening in the expected way, and many are statistically significant. Among the individual-level variables, older individuals have greater odds (OR=1.055, $p<0.01$) of having obtained blood cholesterol screening in the past five years. Men have reduced odds (OR=0.771, $p<0.01$) of having obtained blood cholesterol screening relative to women. Interestingly, blacks have higher odds (OR=1.424, $p<0.01$) of having obtained blood cholesterol screening in the past five years relative to whites. This may be because blacks are more likely to be diagnosed with chronic conditions such as heart disease and high blood pressure (Go et al., 2013). Asians, on the other hand, have lower odds (0.871, $p<0.01$) of having obtained blood cholesterol screening in the past five years relative to whites.

Not surprisingly, individuals with greater educational attainment have higher odds of having obtained blood cholesterol screening across all educational categories, relative to individuals with no high school degree. Specifically, individuals with a high school degree have greater odds of having had their blood cholesterol screened in the past five years (OR=1.390) relative to individuals with no high school degree. Similarly, individuals with some college education have greater odds (OR=1.713, $p<0.01$) of having had blood cholesterol screening in the past five years relative to individuals with no high school degree. Individuals who have obtained a college degree also have greater odds (OR=1.986, $p<0.01$) of having had their blood cholesterol screened in the past five years.

Interestingly, employment status is significantly associated with blood cholesterol screening in Model C. Individuals who are employed and not in the labor market have greater odds of reporting having had their blood cholesterol screened in the past five years relative to the unemployed. However, these variables lose significance in the final specification, after lifestyle and health related variables are included in the model.

Annual household income is positively associated with individuals' having obtained blood cholesterol screening in the past five years. Individuals who report annual household incomes of \$20,000 to less than \$35,000 have greater odds (OR=1.226, $p<0.01$) of having had their blood cholesterol screened in the past five years, relative to those who report annual household incomes of less than \$20,000. Individuals who report having household incomes of \$35,000 to less than \$50,000 have greater odds (OR= 1.518, $p<0.01$) of having had their blood cholesterol screened in the past five years, relative to those who report annual household incomes of less than \$20,000. Similarly, individuals who report household incomes of \$50,000 to less than \$75,000 report greater odds (OR=1.862, $p<0.01$) of having blood cholesterol screening in the past five years compared to those with annual household incomes of less than \$20,000. Also, individuals who report having annual household incomes of \$75,000 or more report over two and a half times greater odds (OR=2.462, $p<0.01$) of having had their blood cholesterol screened in the past five years relative to individuals who report annual household incomes of less than \$20,000.

Results also show that people who are married or living as married report greater odds (OR=1.180, $p<0.01$) of having had their blood cholesterol screened in the past five years. Not surprisingly, individuals with health insurance have nearly three times greater odds (OR=2.858, $p<0.01$) of having had blood cholesterol screening in the past five years. Interestingly, individuals with better health status have lower odds of having obtained blood cholesterol screening in the past five years. Specifically, those reporting fair (OR=0.735, $p<0.01$), good, (OR=0.588, $p<0.01$), very good (OR=0.539, $p<0.01$), and excellent (OR=0.446, $p<0.01$) health status all report lower odds of having had a blood cholesterol screening in the past five years.

Stratified analysis. Results from the stratified analysis based on low and high-income samples are substantively similar to the main results. Specifically, there is no relationship between income inequality and blood cholesterol screening. Findings also suggest that the relationship between unemployment rates and blood cholesterol screening is similar for both income groups, with unemployment exerting a positive effect on individuals' odds of having obtained blood cholesterol screening in the past five years. Results for the age-based stratification are generally consistent with the main results and are presented in Tables A2A and A2B in Appendix B. Results for the health-based stratification are also presented in the Appendix, Tables A2C and A2D.

Colorectal Cancer Screening

The total sample used to examine colorectal cancer screening consists of 217, 934 participants. The sample is limited to participants who are between 50 and 75 years of age, based on the recommendations put forth by the USPTSF (2014b). Table 3A presents descriptive statistics for all variables used in the analysis. The information is reported for the full sample and by endoscopic colorectal cancer screening status.

Descriptive Statistics

Approximately 63% (n=138,286) of individuals between the ages of 50 and 75 report having received endoscopic colorectal cancer exams within the past ten years. The average Gini Coefficient is 58.82, with individuals who obtained screening residing in areas with higher income inequality. The average unemployment rate is 8.76 percent, with individuals who obtained screening residing in areas with higher unemployment rates. Approximately 24% of participants reside in states with low confidence in medicine, 66% of participants reside in states with medium confidence, and nearly 10% of the sample resides in states with high confidence in medicine. About 25% of participants reside in states with low confidence in the media, 63% of participants reside in states with medium confidence, and 12% resides in states with higher confidence in the media. In terms of social trust, almost 13% of participants live in areas with low social trust, 61% live in areas with medium social trust, and 26% live in areas with high social trust. The per capita associational involvement is 0.30 across the sample. There are an average of 92.86 primary care physicians per 100,000 (population). Additionally, about 48% of the sample resides in areas that receive funding for the CRCCP.

Individuals who report having had endoscopic colorectal cancer screening in the past ten years appear to be older, female, and white. They have greater educational attainment, are not in the labor market, and have higher annual household income. They are also married with fewer children in the household. Moreover, they have health insurance and report better health status. There are statistically significant differences between participants who report having received endoscopic colorectal cancer in the past ten years and those who do not.

Multilevel Models

I begin by estimating a variance component model, also known as an intercept only model, that partitions the variance between individuals and states. Because this is a multilevel logistic regression model, the level 1 variance is fixed at the variance of the standard logistic distribution ($\pi^2/3=3.29$). The state-level variance is 0.07 and is significant. The likelihood ratio statistic for testing the null hypothesis that the ICC is equal to zero is 2689.70, with a corresponding p value of less than 0.01. The ICC is 1.94%. Collectively, these statistics suggest that there is significant state-level variance and that the multilevel model is appropriate to use.

Table 3B presents the multilevel model results for endoscopic colorectal cancer screening. Models A and B include the contextual effects of state-level economic conditions and intervening factors, respectively. Interestingly, the addition of state-level economic conditions reduces the state-level variance to 0.06. The addition of social contextual factors in Model B further reduces the state-level variance to 0.02. Model C adds the individual-level socio-demographic and economic variables. Model D, the final specification, adds the individual-level lifestyle and health variables. In the final specification, estimates are conditional on individual-level socio-demographic, economic, lifestyle, and health variables.

Results show no significant relationship between income inequality and endoscopic colorectal cancer screening in any model specification. On the other hand, there is a positive and significant relationship between state unemployment rates and endoscopic colorectal cancer screening. Specifically, a one standard deviation increase in state unemployment rate is associated with about 8% greater odds ($OR=1.078$, $p<0.01$) of individuals' having received a sigmoidoscopy or colonoscopy in the past ten years. This relationship is robust across all model specifications, even after controlling for individual-level socio-demographic, economic, lifestyle, and health characteristics.

Social factors are added in Model B. Individuals residing in states with high confidence in the media have greater odds (OR=1.237, $p<0.01$) of having received an endoscopic colorectal cancer exam in the past ten years compared to individuals residing in states with medium confidence in the media. Residing in areas with high social trust is also associated with greater odds (OR=1.166, $p<0.01$) of having received an endoscopic colorectal cancer exam in the past ten years compared to residing in a state with medium social trust. Primary care physician supply is also significantly associated with having received endoscopic colorectal cancer screening in the past ten years (OR=1.066, $p<0.01$). Additionally, individuals residing in states that receive funding for the CRCCP also have greater odds (OR=1.169, $p<0.01$) of having received endoscopic colorectal cancer screening in the past ten years.

Most of the individual-level variables affect colorectal cancer screening in the expected way and most are statistically significant. Among the individual-level demographic factors, it appears that being older is associated with greater odds (OR=1.056, $p<0.01$) of having received endoscopic colorectal cancer screening in the past ten years. Men have reduced odds (OR=0.890, $p<0.01$) of having received endoscopic colorectal cancer screening in the past ten years. Interestingly, being black is associated with greater odds (OR=1.279, $p<0.01$) of having received colorectal cancer screening in the past ten years relative to whites. This may be due to the higher rates of colorectal cancer seen in this population (CCA, 2014). Asians and individuals of races other than the ones already mentioned also have reduced odds (OR=0.760, $p<0.01$, and OR=0.870, $p<0.01$) of having obtained endoscopic colorectal cancer screening in the past ten years relative to whites.

Individuals with greater educational attainment have higher odds of having received endoscopic colorectal cancer screening in the past ten years. Specifically, individuals with high school degrees have almost 33% greater odds (OR=1.330, $p<0.01$) of having obtained endoscopic colorectal cancer screening relative to those with no high school degree. Individuals with some college education have approximately 57% greater odds (OR=1.572, $p<0.01$) of having obtained endoscopic colorectal cancer screening in the past ten years relative to those with no high school degree. College graduates have almost two times greater odds (OR=1.911, $p<0.01$) of having obtained endoscopic colorectal cancer screening in the past ten years relative to those with no high school degree.

Individuals who are not in the labor market have greater odds (OR=1.136, $p<0.01$) of having obtained colorectal cancer screening in the past ten years relative to those who are unemployed. Interestingly, individuals who are employed have decreased odds (OR=0.876, $p<0.01$) of having obtained endoscopic colorectal cancer relative to those who are unemployed. Annual household income has a positive relationship with individuals' use of endoscopic colorectal cancer screening. Specifically, individuals who report annual household incomes of \$20,000 to less than \$35,000 have 32% greater odds of having had endoscopic colorectal cancer screening in the past ten years (OR=1.322, $p<0.01$), compared to those who report an annual household income of less than \$20,000. Individuals who report household incomes of \$35,000 to less than \$50,000 report approximately 61% greater odds (OR=1.613, $p<0.01$) of having obtained endoscopic colorectal cancer screening in the past ten years relative to individuals with household incomes less than $20,000. Similarly, individuals reporting annual household incomes of $50,000 to $75,000 have nearly two times greater odds (OR=1.925, $p<0.01$) of having obtained endoscopic colorectal cancer screening in the past ten years. Not surprisingly, individuals who report having annual household incomes of $75,000 or more report greater odds (OR=2.446, $p<0.01$) of having obtained endoscopic colorectal cancer screening in the past ten years.

In terms of lifestyle and health characteristics, individuals who are married or living as married have greater odds (OR=1.194, $p<0.01$) of having obtained endoscopic colorectal cancer screening. Having more children in the household is associated with lower odds (OR=0.834, $p<0.01$) of having obtained colorectal cancer screening in the past ten years. As expected, having health insurance is associated with over two times greater odds (OR=2.393, $p<0.01$) of having endoscopic colorectal cancer screening in the past ten years. Interestingly, better health status is generally associated with lower odds of having obtained endoscopic colorectal cancer screening in the past ten years. Specifically, relative to individuals with poor health, individuals in fair (OR=0.939, $p<0.01$), good (OR=0.876, $p<0.01$), very good (OR=0.821, $p<0.01$), and excellent health (OR=0.718, $p<0.01$) have reduced odds of obtaining endoscopic colorectal cancer screening exams in the past ten years.

Stratified analysis. Results from the stratified analysis based on low and high-income samples are substantively similar to the main results. Specifically, there is no relationship between income inequality and endoscopic colorectal cancer screening.

Findings also suggest that the relationship between state-level unemployment rates and endoscopic colorectal cancer screening is similar for both income groups, with unemployment exerting a positive effect on individuals' odds of having obtained endoscopic colorectal cancer screening in the past ten years.

Summary

Collectively, results suggest that the relationships between state-level economic and social conditions, and individuals' use of CP services vary across each of the three CP services examined. Broadly, results indicate that state-level income inequality is negatively and significantly associated with individuals' use of influenza vaccination. State-level unemployment rates are negatively and significant associated with individuals' use of influenza vaccinations, but positively and significantly associated with individuals' use of blood cholesterol screening and colorectal cancer screening. Results also suggest that state-level confidence in the media is an important predictor of CP service use. In addition, state-level social trust and primary care physician supply are important predictors of individuals' use of endoscopic colorectal cancer screening. Also, residing in a state that receives CRCCP funding is significantly and positively associated with individuals' use of CP services. These results are substantively similar across low and high-income samples. In the final chapter, I explore the possible mechanisms that shape the current findings.

Chapter 8: Discussion and Conclusion

"RT this—prevention is key. The #ACA makes most preventive services available at no cost to you."

-Twitter Account of Kathleen Sebelius (2014), Former Department of Health and Human Services Secretary

The Patient Protection and Affordable Care Act (ACA) places CP services at the forefront of health care in the United States. Indeed, as Koh & Sebelius (2010) explain, the ACA "elevates prevention as a national priority, providing unprecedented opportunities for promoting health through all policies." In the context of these exciting possibilities, it is critical to recognize that CP services do not exist solely in the clinical domain, and cost is not the exclusive barrier to use. CP services are unique because they share similarities with both medical treatments and preventive health behaviors. Too often, however, CP services are viewed as medical interventions that individuals choose to access if they desire to improve their health, and the broader social environment within which these services are accessed is ignored. In fact, the majority of research on CP services examines the individual-level determinants of use, finding that a broad range of socio-demographic, economic, and health related characteristics shape individuals' use of these services (Austin et al., 2009; Borjesson & Enander, 2014; Coe et al., 2012; Duport et al., 2008). The main purpose of the current study is to expand understanding of CP service use beyond individual-level determinants to broader macroeconomic and macro-social determinants of use.

Table 4 provides a summary of the main findings. Broadly, findings suggest that statewide economic conditions affect individuals' use of CP services, though the relationship differs based on the economic measure and the outcome examined. This is not surprising because unemployment rates and income inequality capture different features of the economy, and the CP services examined in the current study differ greatly in terms of accessibility, safety, and risk perception[16]. Findings also suggest that some social aspects of the environment, particularly confidence in the media and social trust, shape individuals' use of CP services. Interestingly, it does not appear that social conditions play an intervening role in the pathway through which economic conditions operate on CP service use. It is also important to point out that these broader economic and social factors are important even after controlling for a wide range of individual-level characteristics.

Economic Conditions and CP Service Use

The relationships between state-level economic conditions and individuals' use of CP services varies. Results suggest that state-level income inequality has a significant negative effect on individuals' use of influenza vaccinations. Stratified analyses based on income shows that this finding is consistent for individuals in both high-income groups and low-income groups, suggesting that the effects of income inequality on influenza use are uniform across income levels. Income inequality does not appear to affect blood cholesterol screening and colorectal cancer screening. Further, state-level unemployment is an important predictor for all three CP services, although the direction of the relationship differs based on the CP service examined. Specifically, individuals residing

[16] An overall profile of each CP service is provided in Appendix B, Figures A1 and A2.

in areas with higher state unemployment have reduced odds of obtaining the influenza vaccination. Interestingly, for blood cholesterol screening and colorectal cancer screening, residing in areas with higher state unemployment is associated with greater odds of receiving these services.

Income Inequality and CP Service Use

The mechanisms through which income inequality affects health and health care use remains to be identified. In the current study, findings point to an independent contextual income inequality effect, or what Subramanian and Kawachi (2004) refer to as the "pollution effect" of income inequality on influenza vaccination use. Thus, the hypothesis $H_{1\text{-}3}$ is supported only for individuals' use of influenza vaccinations. It is possible that income inequality affects influenza vaccinations, but not other CP services, because of differences in states' ability to secure influenza vaccination supply. According to the CDC (2013, p. 6), influenza vaccinations are produced and distributed by the private sector, though the agency encourages "influenza vaccine manufacturers and distributors to use a distribution strategy that provides vaccine to all provider types in a comparable timeframe." Because of the wide variability in providers of influenza vaccinations (e.g. private provider officers, retail settings, worksites, hospitals, health departments, and senior centers), it is possible that states with less income inequality have more resources (e.g. different types of providers) that help them to secure influenza vaccine supply. Thus, income inequality may affect the distribution of resources across states, and individuals' use of influenza vaccinations may be especially sensitive to this because vaccine supply is produced and distributed on an annual basis.

Unemployment Rates and CP Service Use

The relationship between state unemployment rates and CP services differs based on the service examined, with state unemployment demonstrating a significant negative effect on individuals' use of influenza vaccinations, but a significant positive effect on individuals' use of blood cholesterol and endoscopic colorectal cancer screening. Thus, the hypothesis H_{1-1} is supported only for influenza vaccinations. The hypothesis H_{1-2} is supported because unemployment rates exert a significant positive effect on individuals' use of endoscopic colorectal cancer screening.

There are many possible explanations for these findings. Researchers put forth the time cost hypotheses that suggests individuals may engage in healthy behaviors during poor economic times because of the reduced opportunity cost of time during these periods (Ruhm, 2000; Vistnes & Hamilton, 1995). Additionally, during recessions, even individuals who do not experience unemployment may experience reduced working hours (Kroll, 2011). If the opportunity cost of time declines and/or there is more time available, individuals may be more likely to invest in health producing activities. This may explain the positive relationship between unemployment rates and individuals' use of blood cholesterol and colorectal cancer screenings in the current study. These services are typically received in a clinical setting. Although blood cholesterol screening does not require a lot of time, it is frequently conducted during an office visit and/or bundled with other clinical tests, and so may require individuals to make time for a health appointment (AHA, 2014; Konrad, 2011). Endoscopic colorectal cancer screenings are invasive and time-intensive medical procedures, often requiring individuals to take time off from routine activities and even requiring extensive support from others. In this way, the positive effects of state unemployment on blood cholesterol and endoscopic colorectal cancer screenings are consistent with the time cost hypotheses. Interestingly, when results are stratified by income, the findings remain consistent—that is, state-level unemployment rates exert a positive effect on individuals' use of blood cholesterol screening and endoscopic colorectal cancer screening for both low-income and high-income groups. Thus, it is also possible that other mechanisms are at play. It could be, for example, that the threat of losing health insurance drives individuals to obtain recommended CP services.

Moreover, it may also be that state-level unemployment affects individuals' risk perceptions, and higher unemployment leads individuals to make more conservative and safer choices in regards to their health. While the available research on this is limited, there is evidence that individuals' risk perception shifts during recessions. A recent report by McKinsey & Company finds that consumers have shifted their spending habits and purchasing behavior to be more conservative in response to the recession (Bohlen, Carlotti, and Mihas, 2009). This may extend to health related behaviors, and it is consistent with some studies that have found reduced likelihood of engaging in risky behaviors during economic recessions (Ruhm, 2000). Two recent studies use Google trends data to examine Americans' Google search behaviors during the recent economic downturn. Findings suggest that individuals' had greater health concerns during the 2008 to 2011 recession (Althouse et al., 2014; Ayers et al., 2013). This hints at the possibility that individuals are more cognizant of their health when unemployment rates are high.

Findings demonstrate a significant negative relationship between unemployment rates and individuals' use of influenza vaccinations. This finding supports the hypothesis

($H_{1\text{-}1}$). Individuals residing in areas with higher state-level unemployment rates have reduced odds of obtaining the influenza vaccination in the past year. There may be several mechanisms at play. First, as explained previously, it is possible that individuals are distracted during distressful economic conditions (Catalano et al., 2003). Consequently, they may be more likely to forego recommended health care services (Catalano et al., 2003). It is also important to remember that influenza vaccinations differ from other types of CP services in many ways. First, they are more easily accessible and it takes less time to receive an influenza vaccination relative to the other CP services examined. In fact, influenza vaccinations can be obtained without appointment at retail stores such as CVS, Target, and Walgreens. Second, influenza vaccinations are themselves viewed to be risky. In fact, there are numerous websites where people voice concerns that the flu vaccine causes illness, and even news reports of individuals' suffering serious side effects after obtaining the vaccine (Solomon, 2014). If individuals residing in areas with higher unemployment rates tend to make more conservative and safer health choices, it is plausible that foregoing the annual influenza vaccination is perceived to be the more conservative and safer health choice.

Social Capital Perspective

In the current study, it appears that there is a relationship between some cognitive elements of social capital and CP service use. Results indicate that confidence in the media is salient across all CP services, but social trust shapes only individuals' use of endoscopic colorectal cancer screening. Thus, hypothesis $H_{2\text{-}1}$ is partially supported. It is supported for confidence in the media for all CP services. It is also supported for the relationship between social trust and individuals' use of endoscopic colorectal cancer screenings. Specifically, findings suggest that individuals residing in states with lower levels of confidence in the media have decreased odds of obtaining influenza vaccinations and blood cholesterol screening relative to individuals residing in areas with medium confidence. For colorectal cancer screening and blood cholesterol screening, individuals residing in areas with higher confidence in the media have greater odds of obtaining these services relative to individuals residing in areas with medium confidence in the media. These findings are consistent with the current literature that point to the importance of the media in shaping health perceptions. In fact, a number of studies find that the media increases public knowledge and awareness of salient health issues, and some studies have found that this influence extends to health behaviors, as well. For example, Hodgson, Lindsay, and Rubini (2007) find that television advertisements are associated with an increase in the average number of emergency department visits. Other research reports that the media can shape individuals' awareness, knowledge, and behavior across a range of health related areas, including smoking, diet, exercise, and some CP services (e.g. mammogram) (Musa et al., 2009). It may also be that individuals who have greater confidence in the media are more likely to search out health information sources, thus improving their knowledge of health.

Findings also suggest that social trust impacts individuals' use of endoscopic colorectal cancer screening. This is consistent with a body of research that suggests social trust affects health (Kawachi, et al., 2008). There are many potential pathways through which this can occur. First, it is possible that social trust is a reflection of communication patterns—that is, greater social trust is indicative of communication through social networks, including health related communication, which improves individuals' awareness of health recommendations. Second, it is possible that social trusts' affects individuals use of colorectal cancer screening, but not blood cholesterol screening or influenza vaccination, due to the time and resource intensive nature of endoscopic screening examinations. Indeed, existing research shows that there are multiple barriers, including psychological and financial, associated with endoscopic colorectal cancer screening, and delay and procrastination are common (Austin et al., 2009; Bridou et al., 2013). Moreover, individuals undergoing endoscopic colorectal cancer screenings are often medicated during the procedure and need greater support post procedure (CCA, 2014). Thus, individuals residing in areas with higher social trust may have access to the social and psychological resources necessary to encourage them to obtain endoscopic colorectal cancer screening exams. It is possible that both of these mechanisms are at play to encourage and facilitate individuals' use of endoscopic colorectal cancer screening.

Broadly, these findings are consistent with social capital theory that suggests social capital exists at broader contextual-levels and can affect health and health behaviors. Social capital can improve individuals' access to health information, allow communities to pool resources to facilitate individuals' health related actions, and may even provide the social resources necessary to access health services (Kawachi, Takao, & Subramanian, 2013; Kawachi, Kim, Coutts, & Subramanian, 2004; Kawachi et al., 2008). Interestingly, social capital does not appear to be an intervening factor in the relationship between state-level economic conditions and individuals' use of CP services.

Neo-Material Perspective

In the current study, I only incorporate one measure of area-level health related resources, primary care physician supply, to examine the neo-material perspective. Not surprisingly, results vary based on the CP service examined. Thus, the hypothesis, $H_{3\text{-}1}$ is supported only for individuals' use of endoscopic colorectal cancer screening. Specifically, after accounting for individual-level health related characteristics, primary care physician supply does not affect individuals' use of influenza vaccinations and blood cholesterol screening. This may be due to the accessibility of influenza vaccinations and blood cholesterol screenings, which can be obtained in a variety of healthcare settings, including retail pharmacies and walk-in clinics. Moreover, these services do not need to be provided solely by primary care physicians. Rather, other health professionals such as nurse practitioners, pharmacists, and physician assistants can provide these CP services, as well. This may help to explain the lack of significant relationships between primary care physician supply, blood cholesterol screening, and influenza vaccinations.

There is a positive relationship between primary care physician supply and endoscopic colorectal cancer screening. This is likely because endoscopic screening exams are usually performed by a gastroenterologist or a primary care physician (American Cancer Society, 2013). Findings also suggest that the CRCCP program is associated with greater odds of individuals' use of endoscopic colorectal cancer screening. Not surprisingly, in states that receive funding for this program, individuals have greater odds of obtaining a colonoscopy or sigmoidoscopy. This suggests that programs targeted towards specific CP recommendations may be effective in increasing use of CP services.

Materialist Perspective

Consistent with Grossman's (1972) model of healthcare demand and Andersen's (1995) behavioral health model, findings suggest that individual-level characteristics, in addition to contextual factors, are salient in shaping individuals' use of CP services. Importantly, findings suggest that individual-level material resources play an important role in shaping individuals' use of CP services. However, the relationships between state-level variables and individuals' use of CP services found in the current study remain significant even after controlling for individual-level material resources, including income, employment, and health insurance. Thus, it is evident that the materialist perspective alone is not enough to explain individuals' use of CP services, and that contextual factors are important predictors of CP services use.

Other Individual-level Factors

Most of the individual-level factors are significant and have the expected signs. Interestingly, across all CP service outcomes examined, individuals with poor health status are more likely to obtain CP services. This may be due to greater interactions with the healthcare system that occur when an individual is in poor health. These interactions may lead to greater awareness of and adherence to health related recommendations. Alternatively, it is also possible that individuals in poor health recognize their limited health stock, and this recognition results in greater investment in health producing activities. This latter perspective is consistent with the HBM, which suggests that individuals' use of preventive services are a result of complex factors, including their perceived susceptibility and vulnerability to illness (Rosenstock, 1974; Rosenstock et al., 1988).

Interestingly, findings also suggest that blacks are more likely to obtain blood cholesterol screening relative to whites. These findings may be due to differences in illness rates between blacks and whites. Specifically, blacks are more likely to be diagnosed with chronic conditions, such as high blood pressure, obesity, and diabetes (Go et al., 2013). The inclusion of blood cholesterol screening as a key component of routine chronic disease management may explain higher rates of screening among this population.

Collectively, findings suggest that while individual-level factors are key in shaping individuals' use of CP services, the broader contextual environment also exerts an influence on CP services. This is consistent with Andersen's (1995) behavioral health model that suggests the external environment, in addition to individual-level behaviors, shape individuals' health behavior. It also suggests that the effect of state-level income inequality and unemployment on health and health behaviors exists even after controlling for individual-level material resources. Thus, the materialist perspective alone cannot explain the relationships between state-level economic conditions and health related behaviors.

Strengths and Limitations

There are several strengths of this study. This is the first study that suggests a significant association between state-level income inequality and individuals' use of influenza vaccination. This association holds after adjusting for individual-level material and health related resources. Moreover, I use a measure of the Gini index that is computed based on IRS tax return data, which is more reliable than other sources of self-reported data that are commonly used to compute this measure. Second, although this is not the first study to examine the relationship between economic conditions and CP services, it is the first to examine how state-level unemployment rates affect the use of specific CP services (e.g. blood cholesterol screening) using a multilevel modeling framework. Moreover, I do not examine CP service use in totality, but rather examine each CP service separately. The differences in findings suggest that CP services are distinct and should be studied as such. Third, this is also the first study to examine the association between various social capital measures and CP services. The majority of research on social capital and health has not examined the relationship between social capital and CP services, and the studies that have done so use ecological or individual-level study designs that do not allow for an understanding of how broader contextual factors shape individuals' use of these services. Additionally, I control for a broad range of individual-level characteristics, specifically, individual-level socio-demographic, economic, lifestyle, and health characteristics. Finally, the study employs multilevel modeling techniques which allow for an assessment of the relationship between contextual factors and individual-level outcomes, while appropriately adjusting standard errors and producing more precise coefficient estimates.

Limitations

There are also a number of limitations associated with the current study. First, as mentioned earlier, the economic measures employed in the current study are standard measures used to assess the state of the economy. Despite this, there are many features of the economy that are not captured by unemployment rates and income inequality. For example, unemployment rates do not capture underemployment or the number of frustrated workers who are no longer actively seeking employment (BLS, 2014). Additionally, while the Gini index captures the degree of overall inequality in a state, it does not distinguish between income transfers that occur in the upper end of the distribution and those that occur in the lower end of the distribution (De Maio, 2007). Further research using alternative measures of income inequality may help to determine whether the results are sensitive to different kinds of inequality.

There are also a number of limitations associated with the social capital measures used in the current study. First, the state-level estimates of social capital are based on pooling data over a large period of time on the assumption that social capital is time-invariant. However, it is possible that there are shifts in social capital over years. If so, estimates of social capital may be imprecise. Pooling data over time was necessary to increase sample size for states, but may have introduced bias into the current study. Relatedly, the social capital data is not representative at the state-level. While I incorporate post-stratification weights based on age, race, and education to adjust for this, there may be other participant characteristics that are not representative at the state-level. This may also bias results[17].

Additionally, some of the social capital measures employed in the current study may have bidirectional effects on use of CP services. For example, because confidence in medicine is a complex construct that includes individuals' interactions, beliefs, and attitudes about the health care system, it is possible that individuals who have greater

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[17] While the possibility for bias exists, it is likely that coefficient estimates are biased downwards, and findings reported in the study represent conservative estimates. This is due to the use of post-stratification weights, which adjust the GSS sample to representative state-level estimates, and the lack of weights used to analyze the BRFSS sample that is not representative at the state-level. (The BRFSS sample is older.)

confidence in medicine may do so because they do not interact much with the healthcare system, while those that have lower confidence in medicine have more interactions with the healthcare system. Thus, this measure by itself may be limited in capturing the relationship between confidence in medicine and individuals' use of CP services. Moreover, within a state, there may be substantial variability in the amount of social capital present in different areas (e.g. cities and neighborhoods). Future research should focus efforts on investigating the effects of social capital at smaller aggregate units.

It is also important to note that the current study does not include individual-level social capital or social support measures. It is possible that if individual-level social support measures were included in the model, the coefficient estimates for state-level social capital would be reduced. Although I do include some proxies such as relationship status (married or living as married), for example, future studies, should aim to collect detailed information on individual-level social support resources so that the relationships between state-level social capital and individuals' use of CP services can be further clarified. Broadly, future research efforts should focus on developing comprehensive measures of social capital, using more detailed questions, and examining social capital at multiple levels of aggregation (e.g. county and neighborhood). Studies that employ individual-level measures of social networks and social support while simultaneously examining the contextual effects on social capital and individuals' use of CP services may provide information on whether the contextual effects of social capital found in this study persist net of individual-level characteristics.

To examine the neo-material perspective that emphasizes the role of area-level resources, I employ one measure for all three CP services examined, primary care physician supply, and an additional measure for colorectal cancer screening, states' participation in the CRCCP. First, there are some broad concerns with this approach because I do not take into account the many health related resources that are available at the state-level. Future studies should incorporate different types of health related resources to determine if there are other such resources that shape individuals use of CP services. For influenza vaccination, for example, it may be possible to obtain data on the availability of retail stores and other health care clinics that provide vaccinations. In regards to the primary care physician supply measure, although this provides important information on the number of active primary care physicians practicing in each state, this measure is constructed using self-reported data from physicians on their primary and secondary specializations. Because this is a self-reported measure, it is possible that physicians misreport their primary specialization (AAMC, 2012). Regarding the CDC's (2014) data on the CRCCP, although I incorporate information on whether a state receives funding for the program, I do not have any detailed information on how much funding is provided to each state and the types of interventions employed. Detailed information would allow for a better understanding of the degree to which additional funding and specific interventions affect individuals' use of colorectal cancer screening.

In addition, there are also a number of limitations associated with the individual-level BRFSS data. First, all the CP service outcomes examined are based on self-reported data, which is subject to recall bias. This is particularly concerning for blood cholesterol screening because there is some evidence to suggest that individuals may misreport their blood cholesterol screening status (Goldman et al., 2006). This can occur, for example, if individuals believe that physician ordered lab tests include blood cholesterol screening, even though there is a possibility they do not. Moreover, blood cholesterol screening is not only a preventive service, but is also used as part of a comprehensive strategy to manage many chronic diseases. It is possible, for example, that individuals who obtain blood cholesterol screening are doing so because they are at increased risk for heart disease. To further complicate matters, there are no standard USPSTF recommendations for blood cholesterol screening, unless individuals are at increased risk. I conduct the analysis based on recommendations from the AHA (2014), but it is possible that some individuals in the sample are obtaining blood cholesterol screening because they are at increased risk for heart disease. Finally, it is also necessary to note that for the present study I focus only on two types of CP services, immunizations and screenings. Future research efforts should examine how economic and social contextual factors shape individuals use of other types of CP services (e.g. other types of immunizations, screenings, behavioral counseling sessions, and chemoprophylaxis)[18].

Additionally, due to data limitations, I employ a cross-sectional research design so causality cannot be assessed[19]. Future research efforts should examine the relationships between economic conditions, social conditions, and CP service use using longitudinal data to minimize possibility of bias.

Policy Implications and Conclusion

[18] In the present study, I examine three CP services, influenza vaccinations, blood cholesterol screenings, and endoscopic colorectal cancer screening. In additional analysis, I also examine how economic and social contextual factors affect other types of CP services such as mammograms and pap smears.

[19] In separate analysis, I also examine the relationships between state-level economic conditions and individual-level CP service use by pooling BRFSS data over time. This is not possible for social capital due to data limitations.

The current study focuses on the economic and social determinants of CP service use. Although the passage of the ACA increases access to CP services through the expansion of health insurance to individuals, there are nonetheless social and economic contextual factors that affect individuals' use of CP services; these factors have received only limited consideration in health policy initiatives. There are a number of policy implications for the current study. First, for individuals residing in areas with higher unemployment and inequality, it may be prudent to incentivize influenza vaccinations to encourage individuals to adhere to recommended guidelines. Alternatively, developing health promotion campaigns to target areas with higher unemployment rates and income inequalities may also help individuals to overcome the barriers to obtaining influenza vaccinations. Additionally, in areas where there is lower unemployment, it may be necessary to encourage individuals to use routine and recommended CP services such as blood cholesterol and endoscopic colorectal cancer screening. It may be that in such areas individuals are overworked and/or less focused on their health. Thus, interventions designed to educate individuals and employers about the importance of adhering to health related recommendations may encourage individuals to obtain CP services.

Findings also suggest that confidence in the media shapes CP service use. Media related interventions designed to inform individuals of recommended CP services might be especially important in spreading awareness of current health related recommendations. Additionally, efforts aimed at increasing confidence in the media in states where there is low confidence might also improve individuals' use of CP services. There are instances where the media encourages use of services that are not necessarily recommended (Colliver, 2008). Such recommendations may affect public attitudes and create confusion and ambivalence (Colliver, 2008). Indeed, in order to effectively shape public attitudes and health behaviors, it is imperative that the media report health service recommendations as accurately and comprehensively as possible. Ensuring that health related information disseminated by the media is accurate may be one way to increase confidence in the media. On a broader level, gaining public trust demands that the media report news in a manner that is perceived to be unbiased.

Finally, the current study highlights the importance of social trust in individuals' use of colorectal cancer screening. Although there are no direct interventions to improve social trust, there are a number of indirect ways to do so. For example, designing neighborhoods in a way that improves walkability has been known to increase social capital (Leyden, 2003). Second, it is possible that investing in more recreational type spaces (e.g. parks, libraries) may help to increase social contact, and consequently, social trust (Leyden, 2003; Kawachi, Takao, and Subramanian, 2013).

In his work, Becker (1993 p.4) notes that recognizing "the social and economic determinants of disease, health and wellness is complex and threatening" and requires "planned social and economic change." The findings of this study suggest that individual-level determinants shape individuals' CP service use, but social and economic contextual factors are also important. Addressing these broader economic and social factors may have cascading and lasting positive effects on the health of all Americans.

Tables

Table 1A. Means and Proportions for Demographics, by Influenza Vaccination (2011) Status[1]

	Influenza Vaccination Status		
	All (N=438,133)	No (N=237,354)	Yes (N=200,779)
State-level Factors			
Gini Index (2001) (Mean)[2]**	56.97	57.04	56.89
Unemployment Rate (2010) (Mean)[3]**	8.85	8.91	8.78
Social Capital Measures[4]			
Confidence in Medicine (%)			
Low*	19.46	19.64	19.25
Medium**	68.37	68.11	68.68
High	12.17	12.25	12.07
Confidence in the Media (%)			
Low**	24.14	24.75	23.41
Medium**	62.62	61.88	63.49
High**	13.24	13.37	13.89
Social Trust (%)			
Low**	12.22	11.85	12.65
Medium**	56.23	57.06	55.26
High**	31.55	31.09	32.09
Per Capita Associational Involvement[5]**	0.31	0.31	0.30
Total Primary Care Physicians per 100,000 (Mean)[6]**	93.82	93.56	94.14
Individual-level Factors			
Age (Mean)	55.44	51.53	60.05
Male**	39.15	41.67	36.19
Hispanic (%)**	6.31	7.40	5.03
Race (%)			
White**	83.41	81.14	86.08
Black**	8.79	10.29	7.03
Asian	1.97	1.99	1.95
Other Race**	5.83	6.58	4.94
Education (%)			
No High School Degree**	8.74	9.36	8.01
High School Degree**	29.98	30.30	27.42
Some College**	26.98	27.78	26.04
College Graduate**	35.30	32.56	38.52
Employment Status (%)			

Unemployed **	6.16	8.01	3.96
Employed**	49.16	54.66	42.66
Not in the Labor Market[7]**	44.68	37.32	53.38
Household Income (%)			
Less than $20,000**	20.14	21.56	18.43
$20,000 to <$35,000*	21.73	22.89	21.53
$35,000 to <$50,000	14.95	14.88	15.03
$50,000 to <$75,000*	15.86	15.74	15.99
$75,000 or greater**	27.33	25.92	29.02
Married or Living as Married (%)**	55.95	55.24	56.78
Number of Children in Household**	0.53	0.63	0.40
Health Insurance (%)[8]**	88.69	83.52	94.79
Health Status (%)			
Poor**	5.83	5.05	6.75
Fair**	13.41	12.41	14.59
Good**	30.59	30.35	30.88
Very Good**	32.41	32.83	31.91
Excellent**	17.76	19.36	15.87

Notes: All individual-level data obtained from the 2011 Behavioral Risk Surveillance System. Contextual level data obtained from various sources. Statistically significant differences in influenza vaccination status were assessed using chi square test and t-tests.

[1:] Influenza Vaccinations are measured by asking respondents if they have received a flu shot or a flu spray in the past 12 months.

[2:] The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The standard deviation for the Gini index is 2.8

[3:] Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The standard deviation for the unemployment rate is 1.8.

[4:] All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned into one of three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation on either side of the overall mean. Following Kawachi et al., (1999), post stratification weights by age, race, and education are applied before grouping states into levels of social capital. Confidence in medicine is assessed by asking respondents about their level of confidence in medicine as an institution. Confidence in media is a composite measure asking respondents about their level of confidence in two institutions, the press and the television. Social trust is assessed by asking respondents about their level of trust in others.

[5:] Per Capita Associational Involvement is based on the total sum of associational involvements for respondents in each state divided by the total number of respondents in each state.

[6:] Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges 2011, State Physician Workforce Data Book. The standard deviation

for primary care physicians per 100,000 is 23.4 across states.
[7:] Not in the labor market includes those respondents who report being a homemaker, student, retired, or unable to work.
[8:] Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.
*p <0.05, **p <0.01

Table 1B. Random Effects Multilevel Models Predicting Influenza Vaccinations[1] (2011), Odds Ratios

Explanatory Variables	Model A	Model B	Model C	Model D
State-level				
Gini Index (2001)[2]	0.961^{+}	0.956*	0.950*	0.954*
	(0.020)	(0.019)	(0.019)	(0.019)
Unemployment Rate (2010)[3]	0.945**	0.921**	0.918**	0.920**
	(0.020)	(0.020)	(0.020)	(0.020)
Confidence in Medicine[4,5]				
Low		0.988	1.014	1.028
		(0.048)	(0.049)	(0.049)
High		0.879	0.912	0.925
		(0.071)	(0.074)	(0.074)
Confidence in the Media[4,6]				
Low		0.895*	0.868**	0.875**
		(0.044)	(0.043)	(0.042)
High		0.945	0.916	0.913
		(0.054)	(0.053)	(0.052)
Social Trust[4,7]				
Low		1.029	1.062	1.065
		(0.056)	(0.058)	(0.058)
High		0.972	0.958	0.958
		(0.053)	(0.052)	(0.051)
Per Capita Associational Involvement[8]		1.042	1.043	1.050
		(0.122)	(0.123)	(0.121)
Total Primary Care Physicians		1.020	1.013	1.008
Per 100,000[9]		(0.018)	(0.018)	(0.018)
Individual-level				
Age			1.029**	1.026**
			(0.000)	(0.000)
Male			0.813**	0.813**
			(0.006)	(0.006)
Race[10]				
Black			0.771**	0.765**
			(0.010)	(0.010)
Asian			1.190**	1.176**
			(0.032)	(0.031)
Other Race			1.005	0.999
			(0.017)	(0.017)
Hispanic			1.056**	1.105**
			(0.017)	(0.019)
Educational Attainment[11]				

High School Degree			1.065**	1.071**
			(0.015)	(0.016)
Some College			1.193**	1.204**
			(0.018)	(0.018)
College Graduate			1.465**	1.499**
			(0.022)	(0.024)
Employment Status[12]				
Employed			1.248**	1.108**
			(0.020)	(0.019)
Not in the Labor Market			1.686**	1.393**
			(0.028)	(0.024)
Annual Household Income[13]				
$20,000 to <$35,000			1.098**	1.086**
			(0.012)	(0.013)
$35,000 to <$50,000			1.179**	1.123**
			(0.015)	(0.015)
$50,000 to <$75,000			1.268**	1.169**
			(0.016)	(0.016)
$75,000 or more			1.458**	1.336**
			(0.018)	(0.019)
Married or Living as Married				1.042**
				(0.008)
Number of Children in Household				1.001
				(0.004)
Health Insurance[14]				2.292**
				(0.031)
Health Status[15]				
Fair				0.932**
				(0.016)
Good				0.813**
				(0.013)
Very Good				0.740**
				(0.012)
Excellent				0.644**
				(0.012)
Constant	0.832**	0.869**	0.095**	0.078**
	(0.018)	(0.037)	(0.005)	(0.004)
Observations	438,133	438,133	373,559	370,435
Random Effects: State				
Variance	0.021**	0.016**	0.016**	0.016**
	(0.004)	(0.003)	(0.003)	(0.003)
Mean Observations per State	8,942	8,942	7,623	7,559
Number of States	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. All individual-level data obtained from the 2011 Behavioral Risk Surveillance System. Contextual level data obtained from various sources.

1: Influenza Vaccinations are measured by asking respondents if they have received a flu shot or a flu spray in the past 12 months.

2: The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The measure has been standardized.

3: Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The measure has been standardized.

4: All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned one of three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation above and below the mean across states. Following Kawachi and colleagues (1999), post stratification weights by age, race, and education are applied prior to grouping states into levels of social capital. Confidence in medicine is assessed by asking respondents about their level of confidence in medicine. Confidence in media is a composite measure asking respondents about their level of confidence in two institutions, the press and the television. Social trust is assessed by asking respondents about their level of trust in others.

5: The reference group is medium confidence in medical institutions

6: The reference group is medium confidence in the press

7: The reference group is medium social trust

8: Per Capita Associational Involvement is based on the total sum of associational involvements divided by the total number of respondents residing in each state.

9: Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges, 2011 State Physician Workforce Data Book. This measure has been standardized.

10: The reference group is white

11: The reference group is no high school degree.

12: The reference group is unemployed

13: The reference group is individuals reporting less than $20,000 annual household income.

14: Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.

15: The reference group is individuals reporting poor health status.

*** p<0.01, ** p<0.05

Table 1C. Random Effects Multilevel Models Predicting Influenza Vaccinations (2011), Low Income-Sample, Odds Ratios

Explanatory Variables	**Model A**	**Model B**	**Model C**	**Model D**
State-Level				
Gini Index (2001)	0.954*	0.951*	0.958*	0.958*
	(0.020)	(0.019)	(0.021)	(0.020)
Unemployment Rate (2010)	0.928**	0.902**	0.910**	0.911**
	(0.020)	(0.020)	(0.022)	(0.021)
Observations	158,229	158,229	155,811	154,070
Random Effects: State				
Variance	0.021**	0.016**	0.018**	0.016**
	(0.005)	(0.004)	(0.004)	(0.004)
Mean Observation Per state	3,229	3,229	3,179	3,140
Number of States	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. The Low-Income Sample includes only those individuals who report having an annual household income of less than $35,000. Models include all other contextual and individual-level characteristics delineated in Table 1B.

Table 1D. Random Effects Multilevel Models Predicting Influenza Vaccinations (2011), High Income Sample, Odds Ratios

Explanatory Variables	**Model A**	**Model B**	**Model C**	**Model D**
State-Level				
Gini Index (2001)	0.959^{+}	0.957*	0.948**	0.951*
	(0.021)	(0.020)	(0.019)	(0.019)
Unemployment Rate (2010)	0.963^{+}	0.941**	0.923**	0.924**
	(0.021)	(0.022)	(0.020)	(0.020)
Constant	0.873**	0.894*	0.099**	0.065**
	(0.019)	(0.039)	(0.006)	(0.005)
Observations	219,719	219,719	217,748	216,365
Random Effects: State				
Variance	0.022**	0.017**	0.016**	0.015**
	(0.005)	(0.004)	(0.003)	(0.003)
Mean Observation Per State	4,484	4,484	4,443	4,415
Number of states	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. The high-income sample includes only those individuals who reported having an annual household income of $35,000 or more. Models include all other contextual and individual-level characteristics delineated in Table 1B.

Table 2A. Means and Proportions for Demographics, by Blood Cholesterol Screening (2011) Status[1]

	Blood Cholesterol Screening Status		
	All (N=453,170)	No (N=66,902)	Yes (N=386,268)
State-level Factors			
Gini Index (2001) (Mean)[2]**	57.01	56.94	57.02
Unemployment Rate (Mean)[3]**	8.86	8.76	8.88
Social Capital Measures[4]			
Confidence in Medicine			
Low**	19.46	18.86	19.56
Medium**	68.47	66.92	68.73
High**	12.08	14.23	11.71
Confidence in the Media (%)			
Low**	23.96	26.89	23.45
Medium**	62.79	61.90	62.94
High**	13.25	11.21	13.60
Social Trust (%)			
Low**	11.97	11.27	12.09
Medium*	56.66	56.26	56.73
High**	31.37	32.47	31.18
Per Capita Associational Involvement[5]**	0.30	0.31	0.30
Total Primary Care Physicians per 100,000 (Mean)[6]**	93.94	91.41	94.38
Individual-level Factors			
Age (Mean)**	55.98	43.40	58.17
Male**	39.07	45.13	38.03
Hispanic**	6.48	12.50	5.43
Race (%)			
White**	83.05	77.62	83.99
Black**	8.98	9.44	8.90
Asian**	2.00	2.70	1.88
Other Race**	5.96	10.24	5.22
Education (%)			
No High School Degree**	8.84	13.67	8.01
High School Degree**	28.99	32.81	28.33
Some College**	26.87	27.51	26.76
College Graduate**	35.30	26.01	36.91
Employment Status (%)			
Unemployed**	6.08	11.71	5.11
Employed**	49.17	58.41	47.57
Not in the Labor Market[7]**	44.74	29.89	47.31
Household Income (%)			
Less than $2000**	20.30	29.82	18.64

$20,000 to <$35,000**	21.83	25.90	21.13
$35,000 to <$50,000**	14.87	14.36	14.96
$50,000 to <$75,000**	15.78	12.83	16.29
$75,000 or greater**	27.22	17.10	28.98
Married or Living as Married (%)**	56.45	50.04	57.56
Number of Children in Household**	0.52	0.90	0.45
Health Insurance (%)[8]**	88.73	67.56	92.38
Health Status (%)**			
Poor**	5.96	3.83	6.32
Fair**	13.62	12.16	13.87
Good**	30.76	32.12	30.53
Very Good**	32.03	31.20	32.17
Excellent**	17.62	20.69	17.10

Notes: All individual-level data obtained from the 2011 Behavioral Risk Surveillance System. Contextual level data obtained from various sources. Statistically significant differences in blood cholesterol screening status were assessed using chi square test and t-tests.

1: The sample includes only individuals who are 20 years of age or older. Responses are coded as yes if participants report having received this service at least once in the past five years.

2: The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The standard deviation for the Gini Index is 2.8

3: Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The standard deviation for the unemployment rate is 1.8.

4: All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned one of three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation above and below the mean across states. Following Kawachi and colleagues (1999), post stratification weights by age, race, and education are applied prior to grouping states into levels of social capital. Confidence in medicine is assessed by asking respondents about their level of confidence in medicine. Confidence in media is a composite measure asking respondents about their level of confidence in two institutions, the press and the television. Social trust is assessed by asking respondents about their level of trust in other people.

5: Per Capita Associational Involvement is based on the total sum of associational involvements for respondents divided by the total number of respondents residing in each state.

6: Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges, 2011 State Physician Workforce Data Book. The standard deviation for primary care physicians per 100,000 is 23.4 across states.

7: Not in the labor market includes those respondents who reported being a homemaker, student, retired, or unable to work.

[8:] Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.
** $p<0.01$, * $p<0.05$, $^{+}p<0.10$

Table 2B. Random Effects Multilevel Models Predicting Blood Cholesterol Screening (2011)[1], Odds Ratios

Explanatory Variables	Model A	Model B	Model C	Model D
State-level				
Gini Index (2001)[2]	1.019	0.993	1.000	1.011
	(0.034)	(0.026)	(0.026)	(0.026)
Unemployment Rate (2010)[3]	1.067[+]	1.064*	1.080**	1.088**
	(0.036)	(0.031)	(0.031)	(0.031)
Confidence in Medicine[4,5]				
Low		1.001	1.032	1.063
		(0.064)	(0.065)	(0.065)
High		0.944	0.974	1.000
		(0.102)	(0.103)	(0.102)
Confidence in the Media[4,6]				
Low		0.838**	0.823**	0.835**
		(0.054)	(0.052)	(0.052)
High		1.128	1.187*	1.185*
		(0.086)	(0.089)	(0.086)
Social Trust[4,7]				
Low		1.052	1.081	1.088
		(0.077)	(0.077)	(0.076)
High		1.019	1.013	1.008
		(0.073)	(0.071)	(0.069)
Per Capita Associational		0.941	0.948	0.969
Involvement[8]		(0.147)	(0.145)	(0.143)
Total Primary Care Physicians		1.093**	1.058*	1.037
Per 100,000[9]		(0.026)	(0.025)	(0.024)
Individual-level				
Age			1.061**	1.055**
			(0.000)	(0.000)
Male			0.766**	0.771**
			(0.008)	(0.008)
Race[10]				
Black			1.368**	1.424**
			(0.025)	(0.027)
Asian			0.880**	0.871**
			(0.030)	(0.030)
Other Race			0.985	0.966
			(0.020)	(0.020)
Hispanic			0.937**	1.032
			(0.018)	(0.021)
Educational Attainment[11]				
High School Degree			1.384**	1.390**

			(0.025)	(0.027)
Some College			1.715**	1.713**
			(0.033)	(0.034)
College Graduate			1.988**	1.986**
			(0.040)	(0.042)
Employment Status[12]				
Employed			1.177**	1.000
			(0.021)	(0.019)
Not in the Labor Market			1.421**	1.024
			(0.027)	(0.021)
Annual Household Income[13]				
$20,000 to <$35,000			1.269**	1.226**
			(0.018)	(0.019)
$35,000 to <$50,000			1.751**	1.518**
			(0.030)	(0.028)
$50,000 to <$75,000			2.324**	1.862**
			(0.042)	(0.037)
$75,000 or more			3.150**	2.462**
			(0.055)	(0.049)
Married or Living as Married				1.180**
				(0.014)
Number of Children in Household				0.951**
				(0.004)
Health Insurance[14]				2.858**
				(0.038)
Health Status[15]				
Fair				0.735**
				(0.021)
Good				0.588**
				(0.016)
Very Good				0.539**
				(0.015)
Excellent				0.446**
				(0.013)
Constant	5.894**	6.110**	0.098**	0.121**
	(0.198)	(0.343)	(0.006)	(0.008)
Observations	453,170	453,170	384,112	380,849
Random Effects: State Variance	0.054**	0.029*	0.027**	0.026**
	(0.011)	(0.006)	(0.006)	(0.005)
Mean Observations Per Group	9,248	9,248	7,839	7,772
Number of States	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. All individual-level data obtained from the 2011 Behavioral Risk Surveillance System. Contextual level data obtained from various sources.

[1]: The sample includes only participants who are 20 years of age or older. Responses are coded as yes if participants report having received this service at least once in the past five years.

[2]: The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The measure has been standardized.

[3]: Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The measure has been standardized.

[4]: All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned one of three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation above and below the mean across states. Following Kawachi and colleagues (1999), post stratification weights by age, race, and education are applied prior to grouping states into levels of social capital. Confidence in medicine is assessed by asking respondents how much confidence they have towards medicine as an institution. Confidence in media is a composite measure asking respondents about their level of confidence in two institutions, the press and the television. Social trust is assessed by asking respondents about their level of trust in others.

[5]: The reference group is medium confidence in medicine.

[6]: The reference group is medium confidence in the press.

[7]: The reference group is medium social trust.

[8]: Associational Involvement is based on the total sum of associational involvements for respondents divided by the total number of respondents residing in each state.

[9]: Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges 2011 State Physician Workforce Data Book. This measure has been standardized.

[10]: The reference group is white.

[11]: The reference group is no high school degree.

[12]: The reference group is unemployed.

[13]: The reference group is individuals reporting less than $20,000 annual household income.

[14]: Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.

[15]: The reference group is individuals reporting poor health status.

** $p<0.01$, * $p<0.05$, $^{+}p<0.10$

Table 2C. Random Effects Multilevel Models Predicting Blood Cholesterol Screening (2011)[1], Odds Ratios (Low-Income Sample)

Explanatory Variables	Model A	Model B	Model C	Model D
Gini Index (2001)	0.978	0.958	0.992	1.001
	(0.036)	(0.029)	(0.026)	(0.025)
Unemployment Rate	1.058	1.056	1.073*	1.082**
(2010)	(0.039)	(0.035)	(0.032)	(0.030)
Constant	4.219**	4.476**	0.154**	0.180**
	(0.155)	(0.282)	(0.010)	(0.013)
Observations	163,869	163,869	161,203	159,377
Random Effects: State				
Variance	0.063**	0.035**	0.027**	0.024**
	(0.013)	(0.008)	(0.006)	(0.005)
Mean Number of Obs.	3,344	3,344	3,289	3,252
Number of state	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. The low-income sample includes only those individuals who reported having an annual household income of less than $35,000. Models include all other contextual and individual-level characteristics delineated in Table 3B.

Table 2D. Random Effects Multilevel Models Predicting Blood Cholesterol Screening (2011)[1], Odds Ratios (High-Income Sample)

Explanatory Variables	**Model A**	**Model B**	**Model C**	**Model D**
Gini Index (2001)	1.039	1.020	1.021	1.034
	(0.035)	(0.029)	(0.027)	(0.027)
Unemployment Rate	1.111**	1.104**	1.081**	1.090**
	(0.038)	(0.035)	(0.032)	(0.032)
Constant	8.000**	8.090**	0.109**	0.091**
	(0.275)	(0.493)	(0.009)	(0.010)
Observations	225,064	225,064	222,909	221,472
Random Effects: State				
Constant (Variance)	0.055**	0.033**	0.027**	0.027**
	(0.012)	(0.007)	(0.006)	(0.006)
Mean Number of Obs.	4,593	4,593	4,549	4,519
Number of States	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. The high-income sample includes only those individuals who reported having an annual household income of $35,000 or more. Models include all other contextual and individual-level characteristics delineated in Table 1B.

Table 3A. Means and Proportions for Demographics, by Colorectal Cancer Screening (2010) Status[1]

	Colorectal Cancer Screening Status		
	All (N=217,934)	No (N=79,648)	Yes (N=138,286)
State-level Factors			
Gini Index (2001) (Mean)[2]**	58.82	58.71	58.89
Unemployment Rate (Mean)[3]**	8.76	8.69	8.80
Social Capital Measures[5]			
Confidence in Medicine (%)			
Low**	24.00	24.45	23.75
Medium	66.29	66.07	66.42
High*	9.70	9.48	9.83
Confidence in Media (%)			
Low**	24.69	25.97	23.96
Medium	62.98	63.13	62.90
High**	12.32	10.90	13.14
Social Trust (%)			
Low**	12.60	13.45	12.11
Medium**	60.80	62.23	59.98
High**	26.60	24.31	27.91
Per Capita Associational Involvement[6]*	0.30	0.29	0.30
Total Primary Care Physicians per 100,000 (Mean)[7] **	92.86	91.04	93.90
Colorectal Cancer Screening Program[8]**	47.80	44.20	49.88
Individual-level Factors			
Age (Mean)**	61.81	60.07	62.82
Male**	38.37	38.95	38.03
Hispanic (%)**	4.62	6.25	3.68
Race (%)			
White**	85.98	83.71	87.29
Black**	8.16	8.72	7.84
Asian**	1.40	1.64	1.26
Other Race**	4.45	5.93	3.59
Education (%)			
No High School Degree**	8.47	11.93	6.48
High School Degree**	29.85	33.42	27.79
Some College	27.00	26.97	27.02
College Graduate**	34.68	27.68	38.70
Employment Status (%)			
Unemployed **	5.51	7.49	4.37
Employed**	44.95	49.25	42.49

Not in the Labor Market[9]**	49.53	43.26	53.14
Household Income (%)			
Less than $20,000**	19.27	26.08	15.35
$20,000 to <$35,000**	21.99	24.17	20.74
$35,000 to <$50,000**	15.93	15.26	16.31
$50,000 to <$75,000**	16.44	14.36	17.64
$75,000 or greater	26.37	20.13	29.96
Married or Living as Married (%)**	59.66	54.31	62.74
Number of Children in Household**	0.16	0.22	0.12
Health Insurance (%)[10]**	91.54	84.24	95.75
Health Status (%)			
Poor**	7.36	8.26	6.68
Fair**	14.88	16.09	14.18
Good	30.55	30.64	30.50
Very Good**	31.25	29.20	32.43
Excellent*	16.07	15.81	16.22

Notes: All individual-level data obtained from the 2011 Behavioral Risk Surveillance System. Contextual level data obtained from various sources. The sample size includes only participants between 50 to 75 years of age.

[1]: Colorectal Cancer Screening is coded yes if participants report having had a colonoscopy or a sigmoidoscopy in the past 10 years.

[2]: The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The standard deviation of the Gini Index is 3.0

[3]: Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The standard deviation of the unemployment rate is 1.8.

[4]: Median Household Income for 2009-2011 obtained from the Bureau of Labor Statistics, Current Population Survey.

[5]: All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned one of three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation above and below the mean across states. Following Kawachi et al., (1999), post stratification weights by age, race, and education are applied prior to grouping states into levels of social capital.

[6]: Per Capita Associational Involvement is based on the total sum of associational involvements for respondents divided by the total number of respondents responding in each state.

[7]: Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges, 2011 State Physician Workforce Data Book. The standard deviation of primary care physicians per 100,000 is 22.4.

[8]: Some states receive special CDC funding through the Colorectal Cancer Control Screening Program.

[9:] Not in the labor market includes those respondents who reported being a homemaker, student, retired, or unable to work.
[10:] Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.
** $p<0.01$, * $p<0.05$, $^{+}p<0.10$

Table 3B. Multilevel Models Predicting Colorectal Cancer Screening[1] (2010), Odds Ratios

Explanatory Variables	Model A	Model B	Model C	Model D
Gini Index (2000)[2]	1.067^{+}	1.004	0.982	0.991
	(0.039)	(0.025)	(0.027)	(0.027)
Unemployment Rate (2009)[3]	1.061^{+}	1.078**	1.079**	1.078**
	(0.036)	(0.026)	(0.028)	(0.029)
Confidence in Medicine[4,5]				
Low		0.905+	0.928	0.934
		(0.051)	(0.056)	(0.057)
High		1.020	1.010	1.021
		(0.096)	(0.102)	(0.103)
Confidence in the Media[4,6]				
Low		0.936	0.896^{+}	0.903^{+}
		(0.054)	(0.055)	(0.056)
High		1.231**	1.232**	1.237**
		(0.083)	(0.089)	(0.090)
Social Trust[4,7]				
Low		0.950	0.924	0.917
		(0.061)	(0.064)	(0.063)
High		1.143*	1.176*	1.166*
		(0.071)	(0.078)	(0.078)
Per Capita Associational		1.063	1.011	1.013
Involvement[8]		(0.144)	(0.147)	(0.148)
Total Primary Care Physicians		1.086**	1.066**	1.066**
Per 100,000[9]		(0.023)	(0.024)	(0.024)
Colorectal Cancer Screening		1.196**	1.165**	1.169**
Program[10]		(0.056)	(0.059)	(0.059)
Individual-level				
Age			1.064**	1.056**
			(0.001)	(0.001)
Male			0.899**	0.890**
			(0.009)	(0.009)
Race[11]				
Black			1.219**	1.279**
			(0.024)	(0.026)
Asian			0.779**	0.760**
			(0.035)	(0.035)
Other Race			0.849**	0.870**
			(0.022)	(0.023)
Hispanic			0.981	1.006

			(0.025)	(0.026)
Educational Attainment[12]				
High School Degree			1.325**	1.330**
			(0.027)	(0.028)
Some College			1.552**	1.572**
			(0.033)	(0.034)
College Graduate			1.825**	1.911**
			(0.039)	(0.043)
Employment Status[13]				
Employed			0.988	0.876**
			(0.022)	(0.021)
Not in the Labor Market			1.385**	1.136**
			(0.031)	(0.027)
Annual Household Income[14]				
$20,000 to <$35,000			1.402**	1.322**
			(0.022)	(0.022)
$35,000 to <$50,000			1.843**	1.613**
			(0.033)	(0.031)
$50,000 to <$75,000			2.302**	1.925**
			(0.042)	(0.039)
$75,000 or more			2.995**	2.446**
			(0.054)	(0.051)
Married or Living as Married				1.194**
				(0.014)
Number of Children in Household				0.834**
				(0.008)
Health Insurance[15]				2.393**
				(0.047)
Health Status[16]				
Fair				0.939**
				(0.022)
Good				0.876**
				(0.019)
Very Good				0.821**
				(0.019)
Excellent				0.718**
				(0.018)
Constant	1.748**	1.545**	0.012**	0.012**
	(0.063)	(0.083)	(0.001)	(0.001)
Observations	217,934	217,934	188,513	187,161
Random Effect State Variance	0.057**	0.022**	0.025**	0.025**

	(0.012)	(0.005)	(0.005)	(0.005)
Mean Number of Observations Per State	4,447	4,447	3,847	3,819
Number of States	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. All individual-level data obtained from the 2010 Behavioral Risk Surveillance System. Contextual level data obtained from various sources. The sample includes only participants between 50 to 75 years of age.

[1:] Colorectal cancer screening is coded yes if participants report having had a colonoscopy or a sigmoidoscopy within the past 10 years.

[2:] The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The measure has been standardized.

[3:] Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The measure has been standardized.

[4:] All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned one of three three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation above or below the mean across states. Following Kawachi and colleagues (1999), post stratification weights by age, race, and education are applied prior to grouping states into levels of social capital. Confidence in medicine is assessed by asking respondents how much confidence they have towards medicine as an institution. Confidence in media is a composite measure asking respondents about their level of confidence in two institutions, the press and the television. Social trust is assessed by asking respondents about their level of trust in others.

[5:] The reference group is medium confidence in medicine

[6:] The reference group is medium confidence in the media

[7:] The reference group is medium social trust

[8:] Per capita associational involvement is based on the total sum of associational involvements divided by the total number of respondents residing in each state.

[9:] Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges 2011 State Physician Workforce Data Book. The measure has been standardized.

[10:] Colorectal Cancer Control Program: States are coded as 1 if they receive funding for this program and 0 otherwise.

[11:] The reference group is white

[12:] The reference group is no high school degree.

[13:] The reference group is unemployed

[14:] The reference group is individuals reporting <$20,000 annual household income.

[15:] Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.

[16:] The reference group is individuals reporting poor health status.

** p<0.01, * p<0.05

Table 3C. Multilevel Models Predicting Colorectal Cancer Screening[1] (2010), Odds Ratios (Low-Income Sample)

Explanatory Variables	Model A	Model B	Model C	Model D
Gini Index (2001)	1.023	0.978	0.979	0.990
	(0.037)	(0.027)	(0.027)	(0.027)
Unemployment Rate (2009)	1.051	1.066*	1.062*	1.059*
	(0.035)	(0.029)	(0.028)	(0.028)
Constant	1.259**	1.140*	0.028**	0.031**
	(0.045)	(0.067)	(0.003)	(0.003)
Observations	78,365	78,365	77,526	76,767
Random Effects: State	0.054**	0.024**	0.024**	0.024**
Variance	(0.012)	(0.006)	(0.006)	(0.006)
Mean Obs. per State	1599	1599	1582	1566
Number of States	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. The low-income sample includes only those individuals who reported having an annual household income of <$35,000. Models include all other contextual and individual-level characteristics delineated in Table 3B.

Table 3D. Multilevel Models Predicting Colorectal Cancer Screening[1] (2010), Odds Ratios (High-Income Sample)

Explanatory Variables	Model A	Model B	Model C	Model D
Gini Index (2000)	1.075*	1.015	0.992	1.000
	(0.039)	(0.028)	(0.028)	(0.028)
Unemployment Rate (2009)	1.093**	1.110**	1.090**	1.091**
	(0.037)	(0.030)	(0.030)	(0.030)
		(0.061)	(0.062)	(0.063)
Constant	2.223**	1.969**	0.013**	0.006**
	(0.079)	(0.118)	(0.001)	(0.001)
Observations	111,541	111,541	110,987	110,394
Random Effects: State				
Variance	0.055**	0.013**	0.006**	0.027**
	(0.012)	(0.118)	(0.001)	(0.006)
Mean Obs. Per State	2,276	2,276	2,265	2,252
Number of States	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. The high-income sample includes only those individuals who reported having an annual household income of $35,000 or more. Models include all other contextual and individual-level characteristics delineated in Table 3B.

Table 4. Summary of Main Findings

Key Explanatory Variables (Contextual)	Individual-level Outcomes: Influenza Vaccination	Blood Cholesterol Screening	Colorectal Cancer Screening
Economic Conditions			
Unemployment Rate	Negative	Positive	Positive
Income Inequality	Negative	No Relationship	No Relationship
Social Conditions			
Confidence in Medicine	No Relationship	No Relationship	No Relationship
Confidence in the Media	Residing in states with low confidence is associated with lower likelihood of obtaining influenza vaccinations	Residing in states with low (high) confidence is associated with lower (higher) odds of obtaining screening	Residing in states with low (high) confidence is associated with lower (higher) odds of obtaining screening
Social Trust	No Relationship	No Relationship	Residing in states with higher social trust is associated with higher odds of obtaining screening
Primary Care Physician Supply	No Relationship	No Relationship	Positive
Colorectal Cancer Screening Program	N/A	N/A	Individuals residing in states with a colorectal cancer screening program have greater odds of obtaining screening

All results based on multilevel logistic regression models where individuals are nested within states. Results are presented only for state-level variables that have a significant relationship with at least one of the outcome variable examined in the current study. All individual-level data obtained from the 2010 or 2011 Behavioral Risk Surveillance System. Contextual-level data obtained from various sources.

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Appendix A: Clinical Preventive Services

Figure A1. CP Service Recommendations

CP Services	Recommendations	Targets
Influenza Vaccination	Annually for all persons older than 6 months, with few exceptions	Influenza
Blood Cholesterol Screening	Recommendations vary. AHA & NCEP recommend once every five years starting at age 20	Coronary heart disease Stroke Atherosclerosis
Endoscopic Colorectal Cancer Screening	Recommendations vary based on specific tests. Screening measures are recommended for all adults between the ages of 50 and 75	Cancer that begins in the colon or rectum

Source: Influenza vaccination and colorectal cancer screening recommendations obtained from USPTSF. Blood cholesterol screening recommendations from AHA & NCEP

Figure A2. Accessibility, Side Effects, Safety and Effectiveness of CP Services

CP Service	Accessibility	Side Effects	Safety and Effectiveness
Endoscopic Colorectal Cancer Screening	Received in clinical settings Performed by physicians Time consuming due to medications Expensive Most individuals cannot resume their daily routines post procedure	Mild side effects Possibility of serious side effects	Generally safe Some rare complications (perforation of the colon and bleeding) Removal of lesions that may not be clinically harmful
Source: CDC, USPSTF, and Colon Cancer Alliance			

CP Service	Accessibility	Side Effects	Safety and Effectiveness
Influenza Vaccination	A variety of healthcare settings Average cost is approximately $30 Vaccine supply concerns	No immediate side effects Mild side effects Possibility of serious effects	Effectiveness is controversial Public perception varies May still contract the flu
Blood Cholesterol Screening	A variety of healthcare settings Bundled with other tests Fasting required Retail settings $25 to $35	No side effects beyond tenderness at injection site	Tests considered to be safe and accurate
Source: CDC, AHA, and NCEP			

Appendix B: Supplementary Analysis

Table A1A. Random Effects Multilevel Models Predicting Influenza Vaccinations[1] (2011), Odds Ratios (Non-Working Age Sample)

Explanatory Variables	Model A	Model B	Model C	Model D
State-level				
Gini Index (2001)[2]	0.955^{+}	0.961^{+}	0.952^{+}	0.954^{+}
	(0.024)	(0.023)	(0.024)	(0.024)
Unemployment Rate (2010)[3]	0.950*	0.919**	0.926**	0.926**
	(0.024)	(0.024)	(0.026)	(0.025)
Confidence in Medicine[4,5]				
Low		1.036	1.051	1.052
		(0.060)	(0.064)	(0.063)
High		0.855	0.865	0.872
		(0.082)	(0.088)	(0.088)
Confidence in the Media[4,6]				
Low		0.867*	0.847**	0.850**
		(0.050)	(0.052)	(0.051)
High		0.951	0.916	0.918
		(0.065)	(0.066)	(0.065)
Social Trust[4,7]				
Low		1.052	1.116	1.100
		(0.069)	(0.077)	(0.075)
High		0.982	0.967	0.969
		(0.063)	(0.066)	(0.065)
Per Capita Associational Involvement[8]		0.934	0.880	0.873
		(0.130)	(0.129)	(0.127)
Total Primary Care Physicians per 100,000[9]		0.987	0.988	0.995
		(0.021)	(0.023)	(0.023)
Individual-level				
Age			1.025**	1.026**
			(0.001)	(0.001)
Male			0.923**	0.890**
			(0.012)	(0.012)
Race[10]				
Black			0.651**	0.647**
			(0.017)	(0.017)
Asian			1.194**	1.156*
			(0.080)	(0.078)
Other Race			0.909**	0.911*
			(0.033)	(0.034)
Hispanic			0.998	0.980
			(0.037)	(0.037)

Educational Attainment[11]				
High School Degree			1.085**	1.109**
			(0.024)	(0.025)
Some College			1.123**	1.171**
			(0.027)	(0.028)
College Graduate			1.276**	1.369**
			(0.032)	(0.035)
Employment Status[12]				
Employed			1.070	1.087^{+}
			(0.053)	(0.055)
Not in the Labor Market			1.474**	1.427**
			(0.070)	(0.068)
Annual Household Income[13]				
\$20,000 to <\$35,000			1.158**	1.158**
			(0.020)	(0.021)
\$35,000 to <\$50,000			1.316**	1.322**
			(0.028)	(0.029)
\$50,000 to <\$75,000			1.410**	1.414**
			(0.034)	(0.036)
\$75,000 or more			1.483**	1.510**
			(0.036)	(0.040)
Married or Living as Married				1.117**
				(0.016)
Number of Children in Household				0.971^{+}
				(0.016)
Health Insurance[14]				1.665**
				(0.083)
Health Status[15]				
Fair				0.943*
				(0.026)
Good				0.835**
				(0.022)
Very Good				0.759**
				(0.020)
Excellent				0.578**
				(0.018)
Constant	1.563**	1.681**	0.155**	0.107**
	(0.040)	(0.084)	(0.016)	(0.012)
Observations	142,259	142,259	110,166	109,220
Random Effects: State				
Variance	0.030**	0.022**	0.024**	0.024**
	(0.007)	(0.005)	(0.006)	(0.005)
Number of Groups	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. All individual-level data obtained from the 2011 Behavioral Risk Surveillance System. Contextual level data obtained from various sources. The non-working age sample consists only of adults who are 65 years of age or older.
[1:] Influenza Vaccinations are measured by asking respondents if they have received a flu shot or a flu spray in the past 12 months.
[2:] The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The measure has been standardized.
[3:] Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The measure has been standardized.
[4:] All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned one of three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation above and below the mean across states. Following Kawachi and colleagues (1999), post stratification weights by age, race, and education are applied prior to grouping states into levels of social capital. Confidence in medicine is assessed by asking respondents about their level of confidence in medicine as an institution. Confidence in media is a composite measure asking respondents about their level of confidence in two institutions, the press and the television. Social trust is assessed by asking respondents about their level of trust in others.
[5:] The reference group is medium confidence in medical institutions
[6:] The reference group is medium confidence in the press
[7:] The reference group is medium social trust
[8:] Per Capita Associational Involvement is based on the total sum of associational involvements divided by the total number of respondents residing in each state.
[9:] Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges, 2011 State Physician Workforce Data Book. This measure has been standardized.
[10:] The reference group is white
[11:] The reference group is no high school degree.
[12:] The reference group is unemployed
[13:] The reference group is individuals reporting less than $20,000 annual household income.
[14:] Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.
[15:] The reference group is individuals reporting poor health status.
*** $p<0.01$, ** $p<0.05$

Table A1B. Random Effects Multilevel Models Predicting Influenza Vaccinations[1] (2011), Odds Ratios (Working Age Sample)

Explanatory Variables	Model A	Model B	Model C	Model D
State-level				
Gini Index (2001)[2]	0.963+	0.950**	0.944**	0.948**
	(0.020)	(0.019)	(0.019)	(0.019)
Unemployment Rate (2010)[3]	0.927**	0.911**	0.913**	0.915**
	(0.020)	(0.020)	(0.020)	(0.020)
Confidence in Medicine[4,5]				
Low		0.958	0.994	1.012
		(0.045)	(0.048)	(0.048)
High		0.906	0.918	0.934
		(0.072)	(0.074)	(0.074)
Confidence in the Media[4,6]				
Low		0.907*	0.881**	0.889*
		(0.043)	(0.043)	(0.042)
High		0.939	0.914	0.908+
		(0.053)	(0.052)	(0.051)
Social Trust[4,7]				
Low		0.999	1.046	1.054
		(0.054)	(0.057)	(0.057)
High		0.970	0.959	0.958
		(0.052)	(0.052)	(0.051)
Per Capita Associational Involvement[8]		1.131	1.119	1.133
		(0.130)	(0.130)	(0.129)
Total Primary Care Physicians per 100,000[9]		1.046*	1.025	1.016
		(0.019)	(0.019)	(0.018)
Individual-level				
Age			1.024**	1.021**
			(0.000)	(0.000)
Male			0.761**	0.760**
			(0.007)	(0.007)
Race[10]				
Black			0.830**	0.817**
			(0.013)	(0.013)
Asian			1.175**	1.169**
			(0.034)	(0.035)
Other Race			1.038*	1.018
			(0.020)	(0.020)
Hispanic			1.065**	1.125**
			(0.020)	(0.021)
Educational Attainment[11]				
High School Degree			1.061**	1.050*
			(0.021)	(0.021)
Some College			1.260**	1.243**

			(0.025)	(0.026)
College Graduate			1.567**	1.563**
			(0.032)	(0.033)
Employment Status[12]				
Employed			1.286**	1.146**
			(0.023)	(0.021)
Not in the Labor Market			1.572**	1.266**
			(0.029)	(0.024)
Annual Household Income[13]				
$20,000 to <$35,000			1.032*	1.014
			(0.015)	(0.016)
$35,000 to <$50,000			1.106**	1.018
			(0.018)	(0.018)
$50,000 to <$75,000			1.215**	1.078**
			(0.019)	(0.019)
$75,000 or more			1.436**	1.273**
			(0.021)	(0.022)
Married or Living as Married				1.029**
				(0.010)
Number of Children in Household				0.997
				(0.004)
Health Insurance[14]				2.318**
				(0.034)
Health Status[15]				
Fair				0.882**
				(0.020)
Good				0.739**
				(0.016)
Very Good				0.670**
				(0.015)
Excellent				0.601**
				(0.014)
Constant	0.615**	0.630**	0.112**	0.104**
	(0.013)	(0.026)	(0.006)	(0.006)
Observations	288,599	288,599	258,747	256,696
Number of Groups	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. All individual-level data obtained from the 2011 Behavioral Risk Surveillance System. Contextual level data obtained from various sources. The working age sample consists only of adults who are 21 to 64 years old.

[1:] Influenza Vaccinations are measured by asking respondents if they have received a flu shot or a flu spray in the past 12 months.

[2:] The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The measure has been standardized.

[3:] Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The measure has been standardized.
[4:] All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned one of three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation above and below the mean across states. Following Kawachi and colleagues (1999), post stratification weights by age, race, and education are applied prior to grouping states into levels of social capital. Confidence in medicine is assessed by asking respondents about their level of confidence in medicine as an institution. Confidence in media is a composite measure asking respondents about their level of confidence in two institutions, the press and the television. Social trust is assessed by asking respondents about their level of trust in others.
[5:] The reference group is medium confidence in medical institutions
[6:] The reference group is medium confidence in the press
[7:] The reference group is medium social trust
[8:] Per Capita Associational Involvement is based on the total sum of associational involvements divided by the total number of respondents residing in each state.
[9:] Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges, 2011 State Physician Workforce Data Book. This measure has been standardized.
[10:] The reference group is white
[11:] The reference group is no high school degree.
[12:] The reference group is unemployed
[13:] The reference group is individuals reporting less than $20,000 annual household income.
[14:] Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.
[15:] The reference group is individuals reporting poor health status.
*** $p<0.01$, ** $p<0.05$

Table A2A. Random Effects Multilevel Models Predicting Blood Cholesterol Screening (2011)[1], Odds Ratios (Non-working Age Sample)

Explanatory Variables	Model A	Model B	Model C	Model D
State-level				
Gini Index (2001)[2]	0.998	0.994	0.988	0.994
	(0.029)	(0.027)	(0.027)	(0.028)
Unemployment Rate (2010)[3]	1.092**	1.089**	1.064*	1.069*
	(0.032)	(0.033)	(0.031)	(0.032)
Confidence in Medicine[4,5]				
Low		1.088	1.086	1.088
		(0.072)	(0.071)	(0.073)
High		0.990	0.948	0.972
		(0.108)	(0.100)	(0.106)
Confidence in the Media[4,6]				
Low		0.861*	0.854*	0.858*
		(0.056)	(0.054)	(0.056)
High		1.085	1.153^{+}	1.183*
		(0.086)	(0.092)	(0.097)
Social Trust[4,7]				
Low		1.097	1.091	1.091
		(0.083)	(0.085)	(0.085)
High		1.014	0.977	0.978
		(0.074)	(0.070)	(0.072)
Per Capita Associational Involvement[8]		0.908	0.818	0.818
		(0.144)	(0.126)	(0.130)
Total Primary Care Physicians per 100,000[9]		1.038	1.025	1.039
		(0.027)	(0.027)	(0.029)
Individual-level				
Age			0.991**	0.991**
			(0.002)	(0.002)
Male			0.795**	0.737**
			(0.022)	(0.022)
Race[10]				
Black			0.953	0.955
			(0.052)	(0.053)
Asian			0.630**	0.589**
			(0.076)	(0.071)
Other Race			0.717**	0.708**
			(0.044)	(0.045)
Hispanic			0.657**	0.649**
			(0.040)	(0.041)
Educational Attainment[11]				
High School Degree			1.158**	1.208**
			(0.047)	(0.051)

Some College			1.341**	1.456**
			(0.061)	(0.068)
College Graduate			1.359**	1.572**
			(0.067)	(0.080)
Employment Status[12]				
Employed			0.932	0.963
			(0.086)	(0.090)
Not in the Labor Market			1.480**	1.371**
			(0.129)	(0.122)
Annual Household Income[13]				
$20,000 to <$35,000			1.390**	1.367**
			(0.046)	(0.047)
$35,000 to <$50,000			1.835**	1.801**
			(0.082)	(0.085)
$50,000 to <$75,000			2.481**	2.424**
			(0.140)	(0.143)
$75,000 or more			2.908**	2.924**
			(0.171)	(0.183)
Married or Living as Married				1.306**
				(0.042)
Number of Children in Household				0.978
				(0.022)
Health Insurance[14]				3.368**
				(0.214)
Health Status[15]				
Fair				0.944
				(0.058)
Good				0.744**
				(0.043)
Very Good				0.589**
				(0.035)
Excellent				0.332**
				(0.021)
Constant	17.051**	17.386**	17.649**	7.470**
	(0.504)	(0.995)	(3.193)	(1.481)
Observations	150,181	150,181	114,641	113,611
State				
	0.035**	0.024**	0.020**	0.021**
	(0.009)	(0.006)	(0.006)	(0.006)
Number of Groups	49	49	49	49

All models estimated with multilevel logistic regression models where individuals are nested within states. All individual-level data obtained from the 2011 Behavioral Risk Surveillance System. Contextual level data obtained from various sources. The non-working age sample consists only of adults 65 years of age or older.

[1:] Responses are coded as yes if participants report having received this service at least once in the past five years.
[2:] The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The measure has been standardized.
[3:] Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The measure has been standardized.
[4:] All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned one of three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation above and below the mean across states. Following Kawachi and colleagues (1999), post stratification weights by age, race, and education are applied prior to grouping states into levels of social capital. Confidence in medicine is assessed by asking respondents how much confidence they have towards medicine as an institution. Confidence in media is a composite measure asking respondents about their level of confidence in two institutions, the press and the television. Social trust is assessed by asking respondents about their level of trust in others.
[5:] The reference group is medium confidence in medicine.
[6:] The reference group is medium confidence in the press.
[7:] The reference group is medium social trust.
[8:] Associational Involvement is based on the total sum of associational involvements for respondents divided by the total number of respondents residing in each state.
[9:] Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges 2011 State Physician Workforce Data Book. This measure has been standardized.
[10:] The reference group is white.
[11:] The reference group is no high school degree.
[12:] The reference group is unemployed.
[13:] The reference group is individuals reporting less than $20,000 annual household income.
[14:] Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.
[15:] The reference group is individuals reporting poor health status.
** $p<0.01$, * $p<0.05$, $^{+}p<0.10$

Table A2B. Random Effects Multilevel Models Predicting Blood Cholesterol Screening (2011)[1], Odds Ratios (Working Age Sample)

Explanatory Variables	Model A	Model B	Model C	Model D
State-level				
Gini Index (2001)[2]	1.027	0.994	1.005	1.017
	(0.036)	(0.026)	(0.027)	(0.026)
Unemployment Rate (2010)[3]	1.055	1.060*	1.079*	1.087**
	(0.037)	(0.031)	(0.032)	(0.031)
Confidence in Medicine[4,5]				
Low		0.988	1.024	1.062
		(0.063)	(0.066)	(0.066)
High		0.967	0.976	1.005
		(0.103)	(0.105)	(0.104)
Confidence in the Media[4,6]				
Low		0.833**	0.820**	0.831**
		(0.054)	(0.053)	(0.052)
High		1.140^{+}	1.190*	1.179*
		(0.087)	(0.091)	(0.087)
Social Trust[4,7]				
Low		1.020	1.067	1.086
		(0.074)	(0.078)	(0.077)
High		1.023	1.013	1.007
		(0.073)	(0.073)	(0.070)
Per Capita Associational Involvement[8]		0.956	0.981	1.007
		(0.148)	(0.153)	(0.151)
Total Primary Care Physicians per Per 100,000[9]		1.116**	1.070**	1.042^{+}
Individual-level		(0.027)	(0.026)	(0.025)
Age			1.068**	1.065**
			(0.001)	(0.001)
Male			0.760**	0.771**
			(0.008)	(0.009)
Race[10]				
Black			1.414**	1.453**
			(0.028)	(0.030)
Asian			0.908**	0.912*
			(0.033)	(0.033)
Other Race			1.002	0.978
			(0.022)	(0.022)
Hispanic			0.967	1.086**
			(0.020)	(0.024)
Educational Attainment[11]				
High School Degree			1.415**	1.378**
			(0.029)	(0.030)

Some College			1.791**	1.713**
			(0.038)	(0.038)
College Graduate			2.106**	1.987**
			(0.047)	(0.047)
Employment Status[12]				
Employed			1.200**	1.012
			(0.023)	(0.020)
Not in the labor market			1.504**	1.082**
			(0.031)	(0.023)
Annual Household Income[13]				
$20,000 to <$35,000			1.256**	1.203**
			(0.021)	(0.021)
$35,000 to <$50,000			1.723**	1.443**
			(0.033)	(0.030)
$50,000 to <$75,000			2.265**	1.741**
			(0.044)	(0.037)
$75,000 or more			3.074**	2.307**
			(0.058)	(0.050)
Married or Living as Married				1.106**
				(0.014)
Number of children in household				0.961**
				(0.004)
Health Insurance[14]				3.011**
				(0.043)
Health Status[15]				
Fair				0.722**
				(0.024)
Good				0.602**
				(0.019)
Very Good				0.574**
				(0.018)
Excellent				0.497**
				(0.016)
Constant	4.358**	4.511**	0.071**	0.080**
	(0.154)	(0.252)	(0.005)	(0.006)
Observations	300,505	300,505	267,703	265,506
Random Effects State Variance	0.060**	0.028**	0.029**	0.026**
	(0.012)	(0.006)	(0.006)	(0.006)
Number of Groups	49	49	49	49

All models estimated with random effects multilevel regression models where individuals are nested within states. All individual-level data obtained from the 2011 Behavioral Risk Surveillance System. Contextual level data obtained from various sources. The working age sample consists only of adults who are 21 to 64 years old.

[1:]Responses are coded as yes if participants report having received this service at least once in the past five years.
[2:] The Gini Index is obtained from Frank (2008) based on individual tax filing data from the Internal Revenue Services. A score of 0 indicates an area with perfect equality while a score of 100 indicates perfect inequality. The measure has been standardized.
[3:] Unemployment Rate for 2010 obtained from the Bureau of Labor Statistics, Current Population Survey. The measure has been standardized.
[4:] All cognitive social capital measures are obtained from the General Social Survey, Years 1990-2010. States are assigned one of three levels of social capital for each measure (high, medium, or low), based on thresholds defined by 1.0 standard deviation above and below the mean across states. Following Kawachi and colleagues (1999), post stratification weights by age, race, and education are applied prior to grouping states into levels of social capital. Confidence in medicine is assessed by asking respondents how much confidence they feel about medicine as an institution. Confidence in media is a composite measure asking respondents about their level of confidence in two institutions, the press and the television. Social trust is assessed by asking respondents about their level of trust in others.
[5:] The reference group is medium confidence in medicine.
[6:] The reference group is medium confidence in the press.
[7:] The reference group is medium social trust.
[8:] Associational Involvement is based on the total sum of associational involvements for respondents divided by the total number of respondents residing in each state.
[9:] Primary Care Physicians Per 100,000 is obtained from the Association of American Medical Colleges 2011 State Physician Workforce Data Book. This measure has been standardized.
[10:] The reference group is white.
[11:] The reference group is no high school degree.
[12:] The reference group is unemployed.
[13:] The reference group is individuals reporting less than $20,000 annual household income.
[14:] Health insurance asks respondents if they have any kind of health care coverage, including health insurance, prepaid plans such as HMOs or government plans such as Medicare or Indian Health Services.
[15:] The reference group is individuals reporting poor health status.
** $p<0.01$, * $p<0.05$, $^{+}p<0.10$

Table A2C. Random Effects Multilevel Models Predicting Blood Cholesterol Screening (2011)[1], Odds Ratios (Good Health Sample)

Explanatory Variables	Model A	Model B	Model C	Model D
Gini Index (2001)	1.036	1.005	1.006	1.014
	(0.035)	(0.027)	(0.026)	(0.026)
Unemployment Rate (2010)	1.068+	1.070*	1.085**	1.092**
	(0.036)	(0.032)	(0.031)	(0.031)
Constant	5.588**	5.748**	0.084**	0.063**
	(0.191)	(0.324)	(0.005)	(0.004)
Observations	362,987	362,987	310,422	308,866
Number of Groups	49	49	49	49

All models estimated with random effects multilevel logistic regression models where individuals are nested within states. The good health sample includes only those individuals who report having good, very good, or excellent health status and are 20 years of age or older. Models include all other contextual and individual-level characteristics delineated in Table 3B.

Table A2D. Random Effects Multilevel Models Predicting Blood Cholesterol Screening (2011)[1], Odds Ratios (Poor Health Sample)

Explanatory Variables	Model A	Model B	Model C	Model D
Gini Index (2001)	0.960	0.945+	0.985	0.991
	(0.034)	(0.028)	(0.028)	(0.027)
Unemployment Rate (2010)	1.031	1.022	1.060+	1.069*
	(0.036)	(0.033)	(0.033)	(0.031)
Constant	7.444**	7.990**	0.150**	0.127**
	(0.263)	(0.494)	(0.013)	(0.011)
Observations	88,381	88,381	72,441	71,983
Number of Groups	49	49	49	49

All models estimated with random effects multilevel logistic regression models where individuals are nested within states. The good health sample includes only those individuals who report having fair or poor health status and are 20 years of age or older. Models include all other contextual and individual-level characteristics delineated in Table 3B.