UNHAPPINESS: THE HIDDEN COST OF NOT HAVING HEALTH INSURANCE COVERAGE

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by

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Department of Public Policy and Administration

Abstract

of

UNHAPPINESS: THE HIDDEN COST OF NOT HAVING HEALTH INSURANCE COVERAGE

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Ngan Lam Thi Tran

Although the United States has the highest health care spending per capita of any industrialized country, there are over 48 million nonelderly Americans lacking health insurance coverage, which translates to more than 18% of the nonelderly being uninsured. Currently, governments around the world are pursuing strategies to incorporate well-being measures to advance public policy, yet there are few studies that focus on the effects of health insurance coverage on well-being. This study fills the gap by exploring the relationship between well-being, health insurance coverage, health care cost, and Medicaid factors in the United States.

Data for this study come from the Centers for Disease Control and Prevention's Behavioral Risk Factor Surveillance System (BRFSS) 2010 survey. The BRFSS houses the world's largest ongoing telephone health survey system with over 350,000 adults interviewed each year. It is designed to measure behavioral risk factors for the adult populations to identify emerging health problems, establish and track health objectives, and develop and evaluate public health policies and programs. In addition to the BRFSS data set, this study also uses data on states' ranking of Medicaid programs from a 2007 report published by the Public Citizen Health Research Group.

Controlling for confounding factors, results from a logistic regression analysis indicated that individuals who could not see a doctor due to cost were 40.7% less likely to be satisfied with life. Similarly, individuals without health insurance coverage were 9.4% less likely to be happy. Moreover, individuals residing in states with a 1-standard-deviation-higher percentage of Medicaid scope of services ranking and Medicaid eligibility ranking have lower odds of being satisfied with life by 6.1% and 2.5%, respectively. However, low-income, self-employed, and unemployed individuals residing in states with better Medicaid rankings were found to be happier. These findings add to the existing literature by suggesting that health insurance coverage, ability to see a doctor, and residency in states with better Medicaid rankings substantially affect individual well-being. These effects held across income categories and health status, which further emphasized their significant influence on happiness. Findings from this study have major implications for where policymakers should focus their attention.

_______________________, Committee Chair
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Chapter One

INTRODUCTION

The Declaration of Independence promised every American the unalienable rights to "Life, Liberty and the pursuit of Happiness," yet the idea of what makes people happy is an elusive and ancient mystery that has captured the heart and attention of many philosophers, economists and psychologists throughout history. Increasingly, many are recognizing that money does not necessarily bring happiness. Robert F. Kennedy eloquently captured the short-comings of Gross National Product (GNP) as a measure of well-being by referring to it as a mere accumulation of material things that counts "air pollution and cigarette advertising…the destruction of our redwood and the loss of our natural wonder in chaotic sprawl…napalm and counts of nuclear warheads," and yet "it measures everything in short, except that which makes life worthwhile" (Kennedy, 1968). Given the lack of well-being measures, there is a growing interest among governments around the world to capture the importance of happiness and well-being by incorporating well-being measures to advance public policy.

As of 2011, 48 million nonelderly Americans lacked health insurance coverage, which means more than one in six, or 18% of the nonelderly were uninsured (DeNavas-Walt et al., 2012). The Council of Economic Advisers' (CEA) projection suggests this number would have risen to about 72 million in 2040 in the absence of health care reform (2009). This alarming uninsured rate among the nonelderly population exists despite the fact that health care spending per capita in the United States (U.S.) is higher than in any other industrialized nation. Currently, U.S. health care expenditures are about 18% of Gross Domestic Product (GDP) and projected to rise sharply. If health care costs continue to grow at historical rates, the share of GDP devoted to health care in the U.S. is projected to reach 34% by 2040 (Council of Economic Advisers, 2009).

High uninsured rates and growing health care costs make quality health care less affordable and accessible for the low-income and minority groups that make up a disproportionate percentage of the uninsured. This increases the disparities in health insurance coverage, health status, and health care delivery across the nation.

Although well-being researchers are finding empirical evidence for the major well-being predictors, there is only one study to date that focuses on the effect of health insurance coverage on happiness and well-being even though major policy concerns stem from these issues. This study fills the gap in well-being literature by further exploring the connection between well-being, health insurance coverage, and health care cost. Regression analyses are used to evaluate the impact of health insurance coverage and health care cost in the context of recently adopted landmark legislation, the Patient Protection and Affordable Care Act (ACA), which aims to reduce the uninsured rate by 50%. By exploring the connection between happiness, health insurance coverage, and health care cost, I hope to contribute depth and relevance to the existing discussion on the evaluation of the desirability of the recent health care reform. To provide the framework for my research, the remainder of this chapter includes a discussion of my research question; a background on the ACA; a description of U.S. health care spending and health outcomes; a discussion of the disparities in health insurance coverage and access to care across the U.S.; an emphasis on California's uninsured population and the ACA's impact to narrow this study's scope of analysis to specific state level; a focus on the uninsured population and the consequences of being uninsured; a dialog that circles back to the probable impact of health care coverage and health care cost on well-being to emphasize the significance of my research question; and lastly, a brief description of the remaining chapters in this study.

Research Question

Unquestionably, health insurance coverage and health care cost have a significant impact on access to health care, health status, and presumably well-being. Lack of health insurance coverage and rising health care cost lead to limited access to health care, which could adversely impact an individual's health. Since health is a robust indicator of well-being, lack of health insurance coverage is likely to also affect well-being. Even if individuals do not get sick, the psychological and financial stress from worrying what would happen if they do get sick can be detrimental. The uninsured are less likely to receive preventive care and services for major health conditions and chronic diseases, and as a result, many suffer serious health and financial consequences. Low-income individuals make up a disproportionately large percentage of the uninsured and health insurance is extremely expensive relative to their incomes, therefore the well-being of these individuals is likely to be substantially impacted. While we presume health insurance coverage and health care cost have an impact on well-being, this effect has not been precisely defined or measured in previous well-being studies. This study bridges the gap by measuring the direct effect of health insurance coverage and health care cost on well-being, thus providing a glimpse of the magnitude of the ACA health care coverage expansion's potential effect on our nation's overall happiness. The benefits of health care coverage, reduced health inequities, and improved overall health outcomes of the population may be much greater than the additional cost required to support the health care expansion. The ACA's central goal is to reduce the number of uninsured individuals in the U.S. Understanding the impact of health insurance coverage on happiness would illuminate the ACA's potential impact on our nation's well-being. Furthermore, I plan to analyze the impact of health insurance coverage across states to determine whether health insurance coverage and health care cost's impact on the well-being of the poor is greater in states with less generous Medicaid benefits.

Affordable Care Act Background

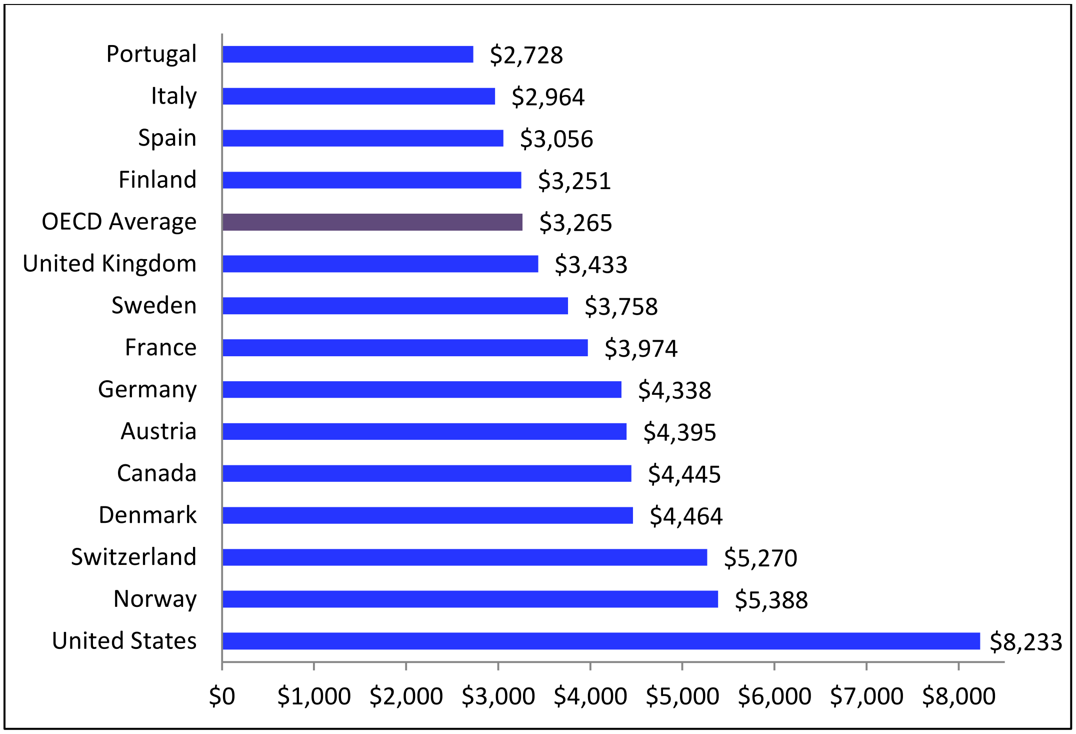
On March 23, 2010, President Obama signed the ACA into law, the most significant and comprehensive health care reform since the passage of Medicare and Medicaid in 1965. Although the ACA already required health plans and insurers to cover individuals regardless of their health status, effective January 1, 2014, the ACA also requires health plan providers to cover a minimum set of services known as the Essential Health Benefits and mandates that most individuals obtain health care coverage or pay a penalty. In addition, the ACA is expected to reduce the uninsured rate by over 50% by expanding Medicaid, providing subsidized private coverage for individuals with incomes up to 400% of the federal poverty level (FPL), and reforming the health insurance marketplace (Congressional Budget Office, 2012). The Congressional Budget Office (CBO) estimated that by 2022, 38 million new individuals would have health coverage, with 12 million through Medicaid and 26 million through the ACA's health insurance exchanges (2013).

To expand coverage, the ACA provides for: (1) the health insurance exchange, a new marketplace in which individuals who do not have access to public coverage or affordable employer coverage can purchase insurance and access federal tax credits, and (2) two expansions of Medicaid – a mandatory expansion by simplifying rules affecting eligibility, enrollment, and retention; and an optional expansion to adults with incomes up to 138% of the FPL. The CBO estimated that the insurance coverage provisions of the ACA would have a net cost of $1.168 trillion over the 2012-2022 period, which accounted for the recent Supreme Court decision that made the Medicaid expansion program optional for states (CBO, 2012). This provision of the Supreme Court decision is estimated to result in 3 million more people being uninsured than the previous estimate under the ACA (CBO, 2012). Overall, the CBO estimated that the ACA would cost about $1.3 trillion over the next 10 years. Despite its cost, the law will reduce the federal budget deficit because it contains provisions for revenue and cost saving measures to offset the increased costs (CBO, 2013).

Health Care Spending and Health Outcome

The U.S. health system and health care delivery is extremely fragmented, with limited public health resources and a large uninsured population. Compared to people in Organisation for Economic Co-operation and Development (OECD) countries, Americans are more likely to find care inaccessible or unaffordable and to report lapses in the quality and safety of care outside of hospitals (National Research Council et al., 2013). Despite its powerful economy, the U.S. has higher rates of poverty and income inequality than most high-income countries, with Americans having less access to “safety net” programs that help buffer the effects of adverse economic and social conditions. Only three OECD countries – Chile, Mexico, and Turkey – provide less health care coverage than the U.S. (National Research Council et al., 2013). What makes the U.S. distinctive is unlike its high-income counterparts, the U.S. does not provide universal or near-universal health insurance coverage, despite spending more per person on health care than any other developed country. Figure 1.1 below, shows the U.S.’ health spending per capita in 2010 was 53% higher than the next highest spending country (Norway) and about 152% higher than the OECD average (OECD, 2013).

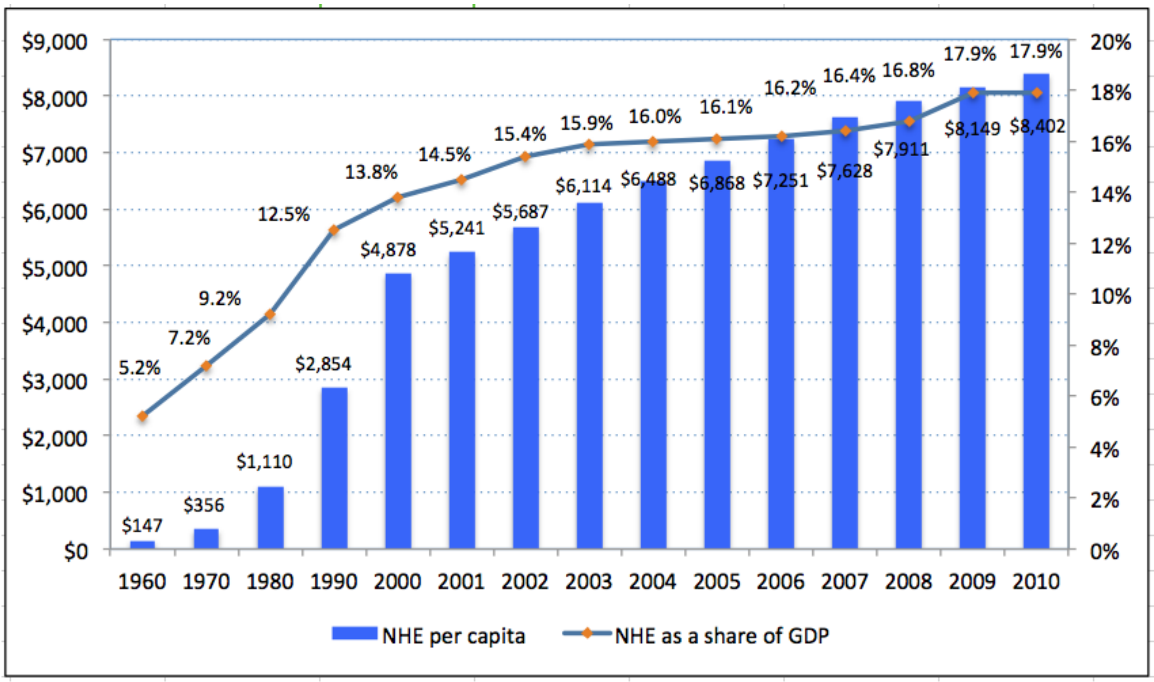
Figure 1.1: Per Capita Total Health Care Expenditures, 2010



Source: Total expenditure on health per capita at current prices and PPPs in U.S. dollars. OECD, 2013.

Since 1950, health care spending more than tripled as a percentage of GDP, with the U.S. government accounting for almost half of all health care spending in the nation (Gruber, 2008; Council of Economic Advisers, 2009). In 1970, total health care spending was about $75 billion, or only $356 per person. In less than 40 years, these costs have grown to $2.6 trillion, or $8,402 per person (see figure 1.2 below). As a result, the share of economic activity devoted to health care grew from 5.2% in 1960 to 17.9% in 2010 and is projected to reach one-fifth of GDP by 2020 (Kaiser Family Foundation, 2012a).

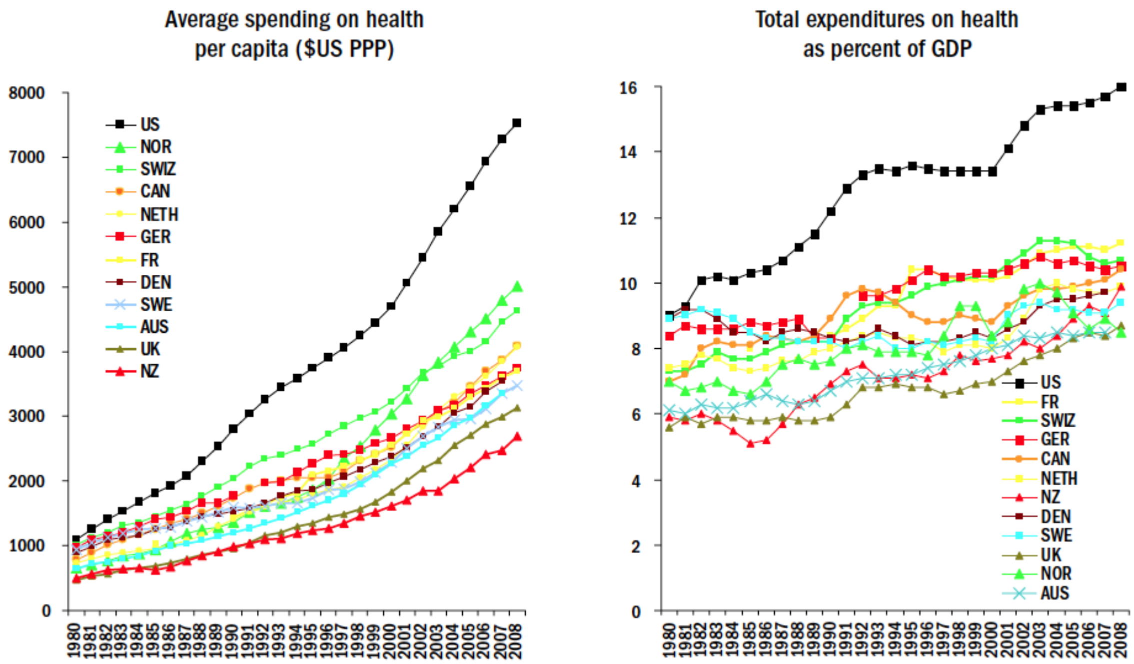
Figure 1.2: National Health Expenditures (NHE) per Capita and as a Share of GDP, 1960-2010



Source: Kaiser Family Foundation, 2012a.

Several sources attributed high health care costs to the inefficiency of the U.S. health care system with payment systems that reward medical inputs rather than outcomes, high administrative costs, and inadequate focus on disease prevention. Compared to 11 other OECD countries from 1998 to 2008, U.S. health care spending growth has considerably surpassed that of other countries, both per capita and as a percentage of GDP (see Figure 1.3 below).

Figure 1.3: International Comparison of Spending on Health, 1980-2008



Source: Squires, D. (2011) - OECD Health Data 2010.
Note: PPP=purchasing power parity, an estimate of the exchange rate required to equalize the purchasing power of different currencies, given the prices of goods and services in the countries concerned.

Although the U.S. health system is the most expensive in the world, comparative analyses indicate its consistent underperformance relative to other countries. Compared to Australia, Canada, Germany, the Netherlands, New Zealand, and the United Kingdom, the U.S. ranked last in the categories of access, patient safety, coordination, efficiency, and equity (Davis, K, et al., 2010). Furthermore, the U.S. ranked at or near the bottom in nine key health indicators: chronic lung disease, drug-related deaths, general disability, heart disease, injuries and homicides, low birth weight, teen pregnancy and sexually transmitted infections, obesity, and diabetes (National Research Council and Institute of Medicine, 2013). Lack of access to health insurance, higher poverty levels, and overeating are among the causes of lower health and shorter life spans among U.S. residents (National Research Council et al., 2013). Between 10 to 50% of U.S. deaths were estimated to occur due to insufficient medical care, while 98,000 lives are claimed each year due to medical errors, such as miscommunications, flawed handoffs, and confusion, resulting in gaps and delays in the delivery of care (National Research Council & Institute of Medicine, 2013).

Table 1.1 below shows the U.S., compared to other high-income countries, have the lowest life expectancy, highest infant mortality rate, highest potential years of life lost due to all causes, highest obesity rate, and is among the countries with the lowest physician density per 1,000 population in 2010 (OECD, 2013).

Table 1.1: OECD Data Comparing the U.S. to 15 Comparable High-Income Countries

	Total health expenditure in 2010 (% of GDP)	Total health expenditure per capita in 2010 (at current prices and PPPs in US dollars)	Public health spending in 2009 (% of GDP)	Physician density per 1,000 population in 2010	Life expectancy in 2010 (years)	Infant mortality, deaths per 1,000 live births	Potential years of life lost in 2010, all causes (male)	Obese population, self-reported (% of total population)
Australia	N/A	N/A	6.2	3.1	81.8	4.1	3,643	21.3
Austria	11.0	4,395	7.3	4.8	80.7	3.9	4,261	12.4
Canada	11.4	4,445	8.0	2.4	80.8	5.1	3,926	17.5
Denmark	11.1	4,464	7.7	3.5	79.3	3.4	4,653	13.4
Finland	8.9	3,251	6.8	3.3	80.2	2.3	4,903	15.6
France	11.6	3,974	9	3.3	81.3	3.6	4,746	12.9
Germany	11.6	4,338	8.6	3.7	80.5	3.4	4,030	14.7
Italy	9.3	2,964	7.4	3.7	82.0	3.4	3,439	10.3
Japan	N/A	N/A	7.1	2.2	83.0	2.3	3,433	N/A
Norway	9.4	5,388	6.2	4.1	81.2	2.8	3,411	10.0
Portugal	10.7	2,728	7.2	3.8	79.8	2.5	4,739	15.4
Spain	9.6	3,056	7.0	3.8	82.2	3.2	3,657	16.0
Sweden	9.6	3,758	7.3	3.8	81.5	2.5	3,073	12.9
Switzerland	11.4	5,270	N/A	3.8	82.6	3.8	3,430	8.1
United Kingdom	9.6	3,433	8.1	2.7	80.6	4.2	3,990	N/A
United States	17.6	8,233	8.3	2.4	78.7	6.1	6,152	28.1
OECD Average	**9.5**	**3,265**	**6.6**	**3.1**	**79.8**	**4.3**	**4,798**	**15.0**

Source: OECD, 2013.

Disparities in Health Insurance Coverage and Health Care Access Across the U.S.

Enacted in 1965 and jointly financed by states and the federal government, Medicaid is the nation's health and long-term care coverage program for over 60 million low-income and high-need Americans (Snyder, et al., 2012). Federal law requires states to cover certain mandatory eligibility groups, including qualified parents, children, and pregnant women with low income, as well as older adults and people with disabilities with low income. Each state establishes and administers its own Medicaid program. Although states must cover certain mandatory benefits, each state has significant flexibility to expand beyond program minimums for benefits and coverage, to determine how care is delivered, and to determine what and how providers are paid. As a result, there is tremendous variation across the states in Medicaid spending, with no evidence of corresponding variations in either medical needs or outcomes.

Taking state population into account, Medicaid spending per state resident varied from a low of $471 in Nevada to a high of $2,595 in the District of Columbia. Medicaid spending per enrollee ranged from a low of $3,527 in California to a high of $9,577 in Connecticut (Snyder, et al., 2012). Across the states, there was nearly a 20-fold difference in eligibility standards for parents, ranging from 11% of FPL in Alabama to 215% of FPL in Minnesota (Courtot, B. & Coughlin, T, 2012). States with a lower uninsured rate were found to have more generous eligibility requirements for Medicaid and other public health insurance programs (Brown, et al., 2000). Table 1.2 below lists states with the highest uninsured rate and states with the lowest uninsured rates.

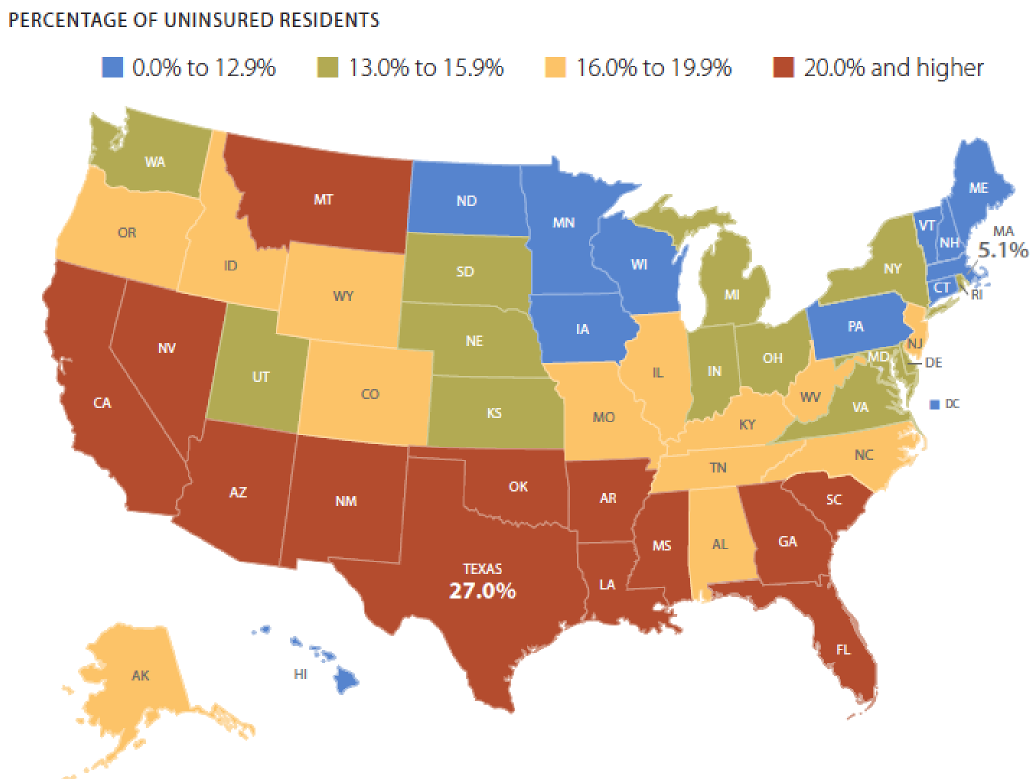
Table 1.2: State Comparison of the Uninsured, 3-Year Average 2009-2011

States with the Highest Percentage of Uninsured Residents	% Uninsured	States with the Lowest Percentage of Uninsured Residents	% Uninsured
Texas	27.0	Massachusetts	5.1
Florida	24.8	Hawaii	8.8
Nevada	24.3	Minnesota	10.3
New Mexico	23.9	Vermont	10.5
Georgia	21.8	Wisconsin	11.1
South Carolina	21.8	Connecticut	11.6
California	21.6	Maine	11.6

Source: Employee Benefit Research Institute, 2012.

The likelihood of being uninsured varies by states due to differences in employment, share of families with low incomes, and public insurance program eligibility levels. Figure 1.4 below shows uninsured rates vary more than five-fold across states ranging from 5% in Massachusetts to 27% in Texas, with states in the South and West having some of the highest uninsured rates.

Figure 1.4: Nonelderly Uninsured Rates by State, 3-Year Average, 2009-2011



Source: California Healthcare Foundation, 2012.

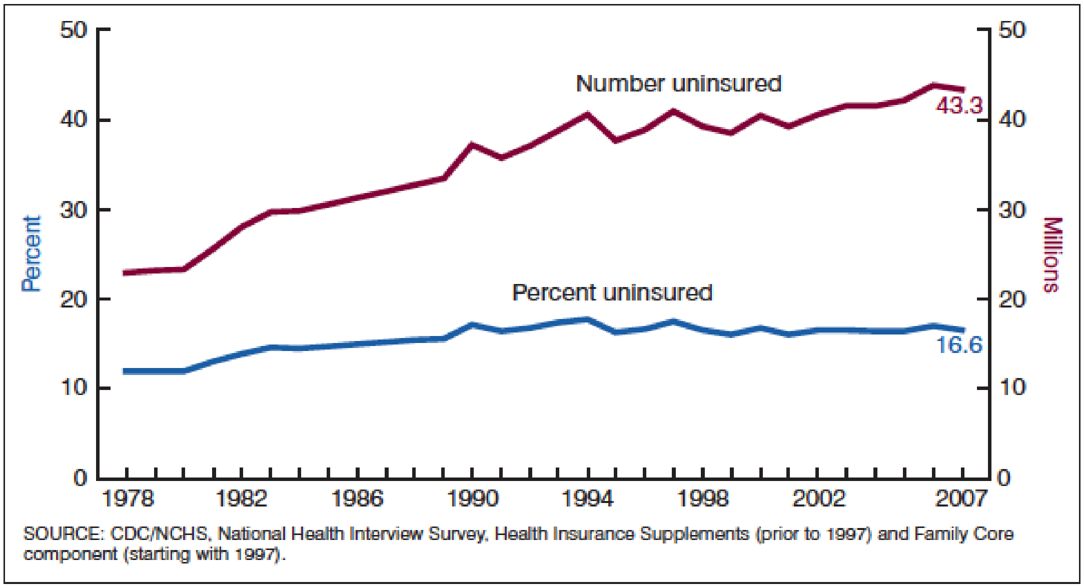
The ACA Medicaid expansion efforts will help narrow the disparity gap of Medicaid benefits and uninsured rates across the states. Although the June 2012 Supreme Court ruling made Medicaid expansion to individuals with incomes up to 138% of the FPL optional for states, many states plan to expand Medicaid eligibility for their residents since the federal government will pay most of the ACA Medicaid expansion expenses. States that do not implement the expansion will forgo significant federal funding.

If all states implement the ACA Medicaid expansion, state Medicaid spending between the years 2013-2022 is projected to increase by $76 billion or less than 3%, while federal Medicaid spending would increase by $952 billion or 26% (Holahan, et al., 2012). States' cost of implementing the Medicaid expansion is relatively small compared to the total states' Medicaid spending, with the federal government paying 93% of the cost. If all states implement the ACA Medicaid expansion, an estimated additional 21.3 million people would enroll in Medicaid by 2022, a 41% increase compared to projected levels without the ACA. This would reduce the number of uninsured by 48% (Holahan, et al., 2012). If no states expand Medicaid, Medicaid enrollment would rise by 5.7 million people, and the number of uninsured would drop by 28% due to increased participation from other ACA provisions (Holahan, et al., 2012). Under given total Medicaid costs with a conservative estimate of $18 billion in state and local savings on uncompensated care, the Medicaid expansion would save states a total of $10 billion over 2013-2022 (Holahan, et al., 2012).

The Uninsured Population

Non-elderly adults (individuals between 18 and 64 years old) make up a disproportionate share of the uninsured population. They are not eligible for Medicare, which is available only to seniors, and are less likely than children to be eligible for Medicaid. Of this group, approximately 56% receive health insurance through employer-sponsored insurance, 20% through Medicaid or other public health programs, 6% through private, non-group markets, and 18% remain uninsured (Kaiser Family Foundation, 2012b). Since 1990, the percentage of nonelderly people without coverage remained stable, but in 2007, the number of uninsured individuals increased by more than six million, to 43.3 million (DeNavas-Walt, et al., 2012) (see figure 1.5 below). During this period, the percentage of private health insurance coverage continued to decline, while the percentage with Medicaid coverage increased. Over the past eleven years, Medicaid coverage has partially offset declining employer-sponsored insurance, but not enough to prevent continued growth in the uninsured population. While 80% of the insured (i.e. 177.8 million people) have coverage through private insurance, only 10% are purchased through private, non-group plans while the majority has employer-provided health insurance (Gruber, 2008). As such, employer-sponsored health insurance is the predominant source of health care and is made possible with a substantial tax subsidy of over $200 billion per year from the federal government to encourage employer-sponsored health insurance (Gruber, 2008).

Figure 1.5: Number and Percentage of Nonelderly without Insurance: U.S., 1978-2007

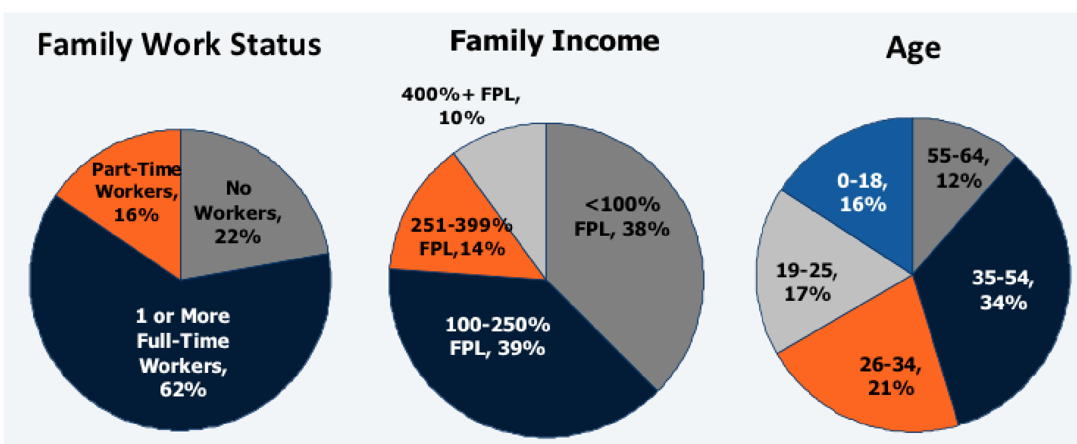


Source: Cohen, et al. 2009.

The recent recession caused the unemployment rate to nearly double from 2007 to 2010, which contributed to a significant decline in employer-sponsored coverage. Because most people receive health insurance through their employers, losing their jobs also means losing their health insurance benefits. Although unemployment contributed to the rise in Medicaid recipients, many remain uninsured due to ineligibility. Between 2007 and 2010, the number of uninsured individuals increased drastically by 5.8 million nonelderly adults (Kaiser Family Foundation, 2012b).

The uninsured population is comprised mainly of the “working poor class” that earns the median income level but is not considered among the poorest in the nation, with 62% in families with one or more full-time workers and 16% in families with part-time workers (Kaiser Family Foundation, 2012b; Gruber, 2008). Nine out of ten uninsured individuals are in low-or-moderate-income families, with individuals below poverty at the highest risk of being uninsured (comprising 38% of the uninsured population) (Gruber, 2008; Kaiser Family Foundation, 2012b). Minorities are much more likely to be uninsured than whites, with about 32% of Hispanics and 21% of African Americans uninsured, compared to 13% of non-Hispanic whites. While the majority of the uninsured population is native or naturalized U.S. citizens, undocumented immigrants accounted for nearly 20% of the uninsured and will continue to remain uninsured as they are not eligible for federally funded health coverage under the health care reform law (Kaiser Family Foundation, 2012b). Figure 1.6, below, shows the characteristics of the nonelderly uninsured population in 2011 by family work status, family income, and age.

Figure 1.6: Characteristics of the Nonelderly Uninsured Population, 2011



Source: The Kaiser Family Foundation, 2012b.

Uninsured adults are far less likely to have had preventive care, including blood pressure, cholesterol, and cancer screenings. Lack of health insurance is associated with a 25% higher mortality risk and is estimated to result in more than 18,000 deaths a year in the U.S. (Institute of Medicine, 2003). Uninsured adults are almost twice as likely to report having fair or poor health compared to those with insurance, with more than a third having a chronic condition. Lack of insurance was also found to adversely impact access to health care. Uninsured individuals are less likely to have a usual source of care and receive timely preventive care, more likely to be hospitalized for avoidable health issues and as a result, uninsured individuals are found to have increased risk of being diagnosed in later stages of disease and have higher mortality rates than those with insurance (Kaiser Family Foundation, 2012b). Additionally, uninsured individuals have greater risk of accumulating unpaid medical bills. Almost half of uninsured individuals are not confident they can pay for needed health care services, compared to 21% of those with health insurance (Kaiser Family Foundation, 2012b).

The rapid growth of health care costs is also driving this downward trend of health insurance coverage in both the private and public sectors, making it increasingly difficult for employers to offer affordable health insurance coverage to their employees. Between 1999 and 2008, the average annual employee premium contribution for family coverage rose from $1,543 to $3,254, far exceeding growth in family incomes (Institute of Medicine, 2009). Individuals without employer-sponsored health insurance who are ineligible for public insurance must rely on a limited non-group health insurance market to obtain coverage. Without employers' contribution, these individuals absorb the entire cost of non-group health insurance premiums. Furthermore, because of irregularities in the U.S. health insurance market, the total cost of non-group health insurance is often significantly higher than equivalent group coverage. Additionally, private insurance in the U.S. has administrative costs averaging 12% of premiums paid, compared to 1.3% in Canada (Gruber, 2008). Through adverse selection in the insurance market, insurers raise premium costs to screen potential applicants and to account for high-risk individuals who are more likely to seek insurance. Asymmetric information causes adverse selection in the insurance market, making it difficult for healthy people to receive actuarially reasonable rates and thus less likely to purchase health insurance. As a result, rising health insurance costs accounted for two-thirds of the lack of insurance observed in the U.S. (Gruber, 2008).

In 1986, Congress enacted the Emergency Medical Treatment and Labor Act (EMTALA) to ensure public access to emergency services regardless of ability to pay. Health care provided by hospitals or other health care providers that remain unpaid because individuals do not have insurance and cannot otherwise afford to pay the cost of care is known as uncompensated care. Uncompensated care amounted to about $57 billion in 2008, 75% of which was eventually reimbursed by federal, state and local funds appropriated for care of the uninsured population (Kaiser Family Foundation, 2012b; Holahan & Garrett, 2010). The remaining cost came from other sources such as physicians, which is in-kind contributions of doctors, and private funding, such as reimbursement from financial surpluses on private patients (Holahan & Garrett, 2010). Without health care reform, uncompensated care is estimated to cost between $560 billion to $700 billion for the six-year period from 2014 to 2019 (Holahan, et al., 2010). Due to implicit insurance provided through uncompensated hospital care, individuals may forgo purchasing health insurance if their medical risks are primarily catastrophic. Thus, individuals are more likely to be uninsured in communities where more free care is delivered (Gruber, 2008). This adds a multiplier effect through adverse selection, where the unhealthiest choose not to insure and instead rely on free care. As a result, prices are raised for the remaining individuals demanding insurance.

California's Uninsured Population and the Projected Impact of the ACA

California's uninsured rate of 22% is significantly higher than the national average uninsured rate of 18% among the nonelderly population. In 2011, more than one in five

Californians was uninsured (California Healthcare Foundation, 2012). California has the largest total number of uninsured and the seventh largest uninsured percentage in the nation, with Texas and Florida leading at 27% and 24.8% (California Healthcare Foundation). The percentage of uninsured Californians has risen steadily over the past two decades. Latinos are much more likely to be uninsured than other ethnic groups, comprising nearly 60% of California's uninsured population, with nearly one in three uninsured (California Healthcare Foundation). California workers' likelihood of being uninsured is 24%, compared to the national average of 19%. Additionally, Californians with annual family incomes below $25,000 are most likely to be uninsured.

Currently Medi-Cal, California's Medicaid program, delivers comprehensive health care services at no or low cost to 21.7% of the state's total population, approximately eight million low-income individuals or one in five Californians. This includes families with children, seniors, persons with disabilities, children in foster care, and pregnant women. Since Fiscal Year 2006-07, total Medi-Cal spending from all sources grew 10.6% annually to $55.9 billion in 2012-13 (Brown Jr., 2013). Medi-Cal General Fund spending is projected to increase 3.9% from $15 billion in 2012-13 to $15.6 billion in 2013-14 (Brown Jr., 2013). California pays a relatively greater share of its Medi-Cal cost than other large states, receiving only the minimum 50% federal funding for Medi-Cal costs, compared to the national average of 57% (Brown Jr., 2013). Although Medi-Cal cost per case of $4,539 in 2012-13 is substantially lower than the national average, California's eligibility rules are relatively more generous.

California was also the first state to pass laws implementing the health benefit exchange. In 2014, California's health benefit exchange, Covered California, will begin providing insurance to nearly one million Californians. In January 2013, Governor Jerry Brown released a budget proposal that included $350 million in General Funds to implement the federally mandated expansion of Medicaid coverage. The budget also included the optional expansion of Medi-Cal to individuals with incomes up to 138% of the FPL. Under the ACA, the federal government will initially pay 100% of the cost for newly eligible individuals with funding gradually decreasing to 90% by 2020, although states will bear a portion of the expansion costs on a permanent basis. New state Medi-Cal spending will be between $188 and $453 million in 2014 and slightly higher in 2015 and 2016. This will be largely offset by increased tax revenues, new federal dollars, and savings in other areas of the budget, including other state health programs, mental health, and state prisons (Lucia, et al., 2013).

Table 1.3 below shows the projected impact of the ACA on insurance coverage in California by 2016, which is the first year the ACA will be fully phased in. Under the ACA, an additional 3.4 million people in California will be insured by 2016, equivalent to nearly 96% of documented residents under age 65 (Long & Gruber, 2010). Enrollment in Medi-Cal is expected to increase by 1.7 million people, while 4 million are projected to enroll in the state's planned new insurance exchange along with a decline of 2.2 million from employer-sponsored and traditional non-group coverage (Long & Gruber, 2010). Since the ACA provisions exclude undocumented residents, this group would account for a disproportionate share of the uninsured in California, at 19% compared to a national average of 10%. Even with health care reform, 1.2 million undocumented Californians would remain uninsured (Long & Gruber, 2010).

Table 1.3: Projected Changes in Insurance Coverage in CA by 2016 as a Result of the ACA

	Millions of people in California		
Type of coverage	**Without the law**	**With the law**	**Impact of the law**
Employer-sponsored	18.90	18.03	−0.87
Traditional nongroup	2.24	0.87	−1.37
Exchange	0.00	4.01	4.01
Public	6.58	8.29	1.71
None	6.53	3.10	−3.43

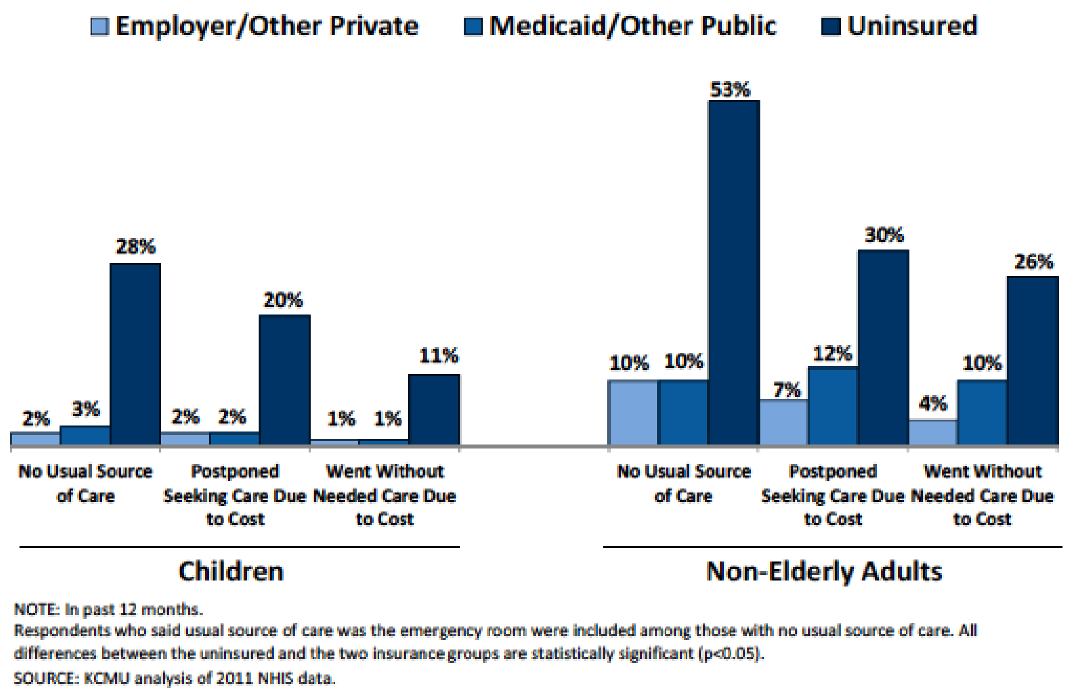
Source: Long & Gruber, 2010.

Consequences of the Uninsured

Societies should be concerned about the uninsured because there are many unintended consequences related to the lack of health insurance. Externality is a side effect or consequence of an economic activity that is experienced by unrelated third parties not involved in the transaction. When these effects are positive, they are called positive externalities while negative effects are called negative externalities. Lack of health insurance results in negative physical and financial externalities. Physical externalities are associated with communicable diseases as uninsured individuals are less likely to receive vaccinations and care for these diseases (Gruber, 2008). Financial externalities are the substantial uncompensated care when the uninsured cannot pay their medical bills. Other financial externalities include lowered productivity as a result of inefficiencies in the labor market since individuals are locked to their job for fear of losing health insurance, a phenomenon known as “job lock” that results in mismatches between workers and jobs (Gruber, 2008).

Furthermore, spillover costs of the uninsured are experienced within communities resulting in poorer health of the uninsured population and increased demands on local public budgets and on providers to support care for the uninsured. Those living in communities with a higher than average uninsured rate are also at risk of reduced access to health care services and overtaxed public health resources. In 2011, 26% of uninsured nonelderly adults did not receive or delayed seeking needed care due to cost, compared to only 4% of adults with private coverage and 10% of adults with Medicaid (Kaiser Family Foundation, 2013). National data suggested that the uninsured were much more likely to report not having a usual source of care, delaying, and forgoing needed care due to cost (see Figure 1.7 below). Undiagnosed health problems associated with lack of insurance could cost significantly more when treated later.

Figure 1.7: Access to Care by Health Insurance Status, 2011



Source: Kaiser Family Foundation, 2013.

Public health is a non-excludable public good that benefits everyone in the community. It is characterized by adding value that benefits the community beyond any price paid, requiring large initial investment costs that are too expensive for any individual or corporation to afford and earn a reasonable return, requiring a higher level of administration than any individual or company can arrange, and having value that accrues over time that is difficult to assess. Because of market inefficiencies and the inability for any entity to meet the demand of public health, the public's health care needs have to be met through other means to ensure everyone has access to affordable basic health care. The Council of Economic Advisers estimated that extending health care coverage to the uninsured population will reduce financial risk for the uninsured by $40 billion annually, save over $180 billion annually from averting preventable deaths caused by lack of health insurance, and increase net economic well-being by approximately $100 billion a year

(2009). Thus, extending coverage to the uninsured population could potentially generate substantial benefits far exceeding its costs. From a policy perspective, the health disadvantage among low-income individuals drives the necessity to redistribute health care resources to lower income groups that tend to be uninsured. Moreover, physical externalities associated with communicable diseases and financial externalities of uncompensated care are extremely costly to society (Kaiser Family Foundation, 2012b; Gruber, 2008).

Health Care Coverage, Health Care Cost, and Well-Being

As a society, Americans spend a great deal of resources on health care with health outcomes that are worse than other industrialized countries. Even though greater health care spending contributes to higher GDP, it is clear that increased GDP does not necessarily improve our society's health outcomes. We place significant emphasis on economic measures to assess our country's progress and development. However, American happiness level has not changed much over the last four decades despite large increases in real income per capita. Moreover, some services and products included in GDP actually lower our well-being rather than improve it, such as expenditures on warfare, catastrophes, and economic activities with negative externalities. While GDP represents the nation's overall output and productivity, it does not explain how that wealth is distributed and fails to capture other non-economic well-being factors, such as equity in access to health care, health status, leisure, security, and a sustainable environment.

In the first ever World Happiness Report, commissioned in 2012 for the United Nations Conference on Happiness, the Earth Institute survey ranked 156 countries on quality-of-life barometers that promote human well-being based on the Gross National Happiness (GNH) concept introduced to the UN by the King of Bhutan. GNH is grounded on the premise that wealth calculation should consider other aspects besides economic development, such as the preservation of the environment and the quality of life of the people. Based on this new ranking, the happiest countries in the world are all in Northern Europe (Denmark, Norway, Finland, Netherlands) and the least happy countries are all poor countries in Sub-Saharan Africa (Togo, Benin, Central African Republic, Sierra Leone), with the U.S. ranking 11th in the new happiness index (Earth Institute, 2012). The report highlights the U.S. as a case in point where higher average incomes do not necessarily improve average well-being, since measures of average happiness remained unchanged over half a century despite the fact that the U.S. GNP per capita has risen by a factor of three since 1960, a period in which inequality has soared, social trust has declined, and the public has lost faith in its government (Earth Institute, 2012).

To date, various governments are making conscious efforts to measure their citizens' levels of happiness and well-being in order to implement policies to improve quality of life. However, despite the increased attention to happiness, it remains somewhat unclear what policy measures enhance or reduce it. This is a critical question if governments are to improve their citizens' quality of life. Currently, happiness research indicates that GDP should not be the only economic measure to consider when examining the health and well-being of a society. Rather, policymakers may want to ponder other aspects of a society that can be improved by government to increase societal well-being and quality of life. For example, will a society's overall well-being increase if there is more emphasis on reducing income inequality, increasing access to healthcare, raising education quality, and improving public transportation?

This study aims to provide some answers to the question of what influences happiness and well-being. Particularly, I will be focusing on the impact of health insurance coverage and health care cost on individual well-being as part of a broader effort to understand the impact of the ACA's Medicaid expansion on societal well-being. I expect that these factors play a pivotal role in contributing to individual well-being. Understanding the role and significance of health insurance coverage and health care cost on individual happiness could enhance existing well-being literature, particularly adding nuances and depth to health's impact on well-being. Studying the impact of health insurance coverage and health care cost on well-being is a timely policy focus, especially since one of the most historic and expansive pieces of health care legislation goes into effect on January 1, 2014.

Organization of Thesis

In the next chapter, I discuss the literature on key predictors of individual well-being, with particular emphasis on the role of health status and health insurance coverage on happiness. In Chapter three, I describe the source of my data, the functional form of my regression model, and the rationale and relevancy of the dependent variables included in the model. In the results chapter, I describe the outcomes of my regression analysis, along with a discussion of adjustments made to the original model and potential problems with the model results. I conclude with the policy implications based on my findings, along with study limitations and further research.

Chapter Two

LITERATURE REVIEW

This literature review examines the definition and measurement validity of happiness and provides a discussion of the key causal variables that have been included in other well-being studies. The review is focused on five central themes: (1) defining happiness and measurement validity of happiness; (2) policy implications of happiness research; (3) key happiness predictors; (4) health effect on well-being; and (5) gaps in happiness and well-being literature. The first theme serves to define the idea of happiness and well-being as well as addressing the validity of existing data collected on this subject. The second theme focuses on why happiness research matters from a policy perspective. The third theme highlights the key determinants of happiness and well-being. The fourth theme centers on health's effect, which is the well-being determinant most related to this study's key predictors. The last theme underlines the gap in the literature and how this study could help bridge that gap. My review is particularly focused on studies that utilize regression analyses, as I will be developing my own regression model to assess the impact of health insurance coverage on happiness and well-being. Appendix A provides a summary of the literature discussed in this study.

Defining Happiness and Measurement Validity

Defined

Diener (1997), the dean of American happiness scholars, defined a person as having high well-being or happiness if he or she experiences life satisfaction, frequent joys and infrequent unpleasant emotions such as anger or sadness. On the contrary, a person with low well-being is dissatisfied with life, experiences frequent negative emotions such as anger and anxiety and infrequent joy or affection (Bok, 2010). In most happiness studies, the terms happiness, well-being, subjective well-being (SWB), and life satisfaction are used interchangeably to describe how happy people feel and how satisfied they are with their life. To understand the forces that affect societal well-being, these studies aim to determine characteristics of happy individuals and how government can apply research findings at the individual level to improve overall societal well-being. Happiness data are subjective self-reported measures with no specific definition or value assigned to each happiness level, such as what it means to be very happy, pretty happy, and not too happy. The underlying notion is that people have their own idea of what "happiness" and "the good life" are, and it is reasonable to infer that people are the best judges of their overall quality of life. Therefore it is best to ask individuals directly about their own happiness and life satisfaction.

Measurement Validity

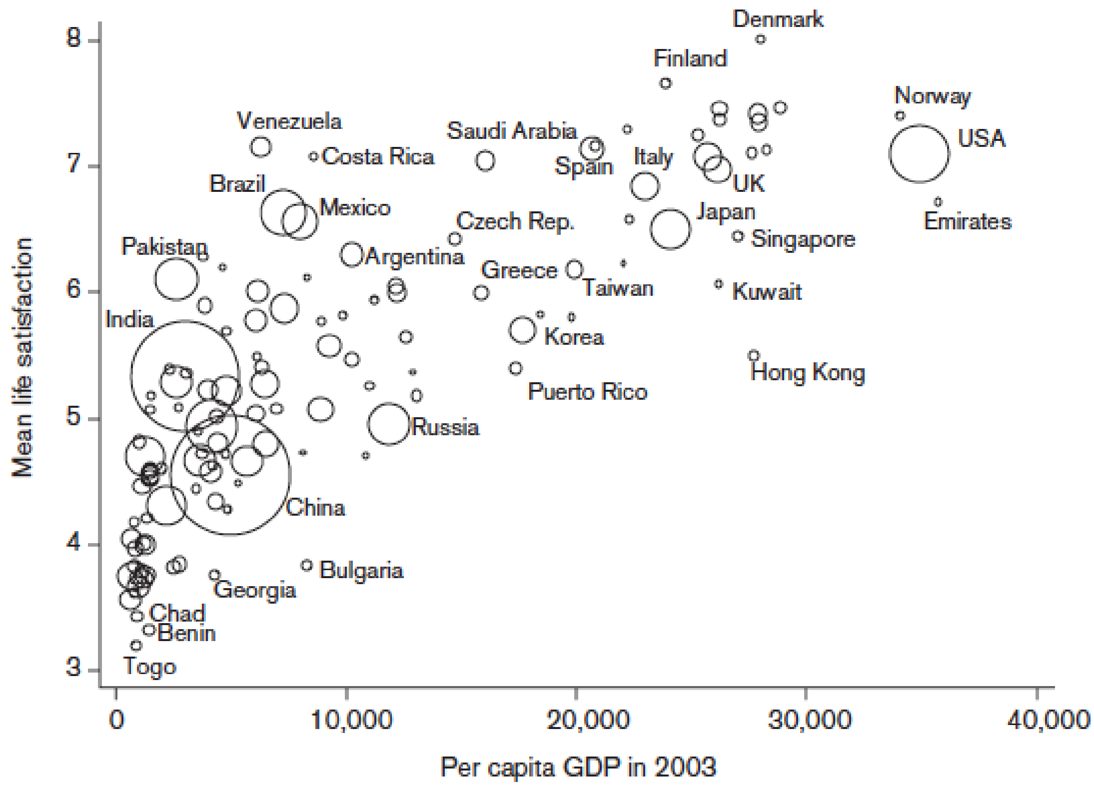
Surprisingly, my review of the literature found highly reliable and valid measurements of SWB and happiness. Although happiness is typically measured as a single item with fixed response categories, happiness instruments have been used widely in well-being research around the world. According to Bottan and Truglia (2011), SWB measures have been shown to correlate with more objective measures of well-being. Consistency tests indicate that recorded happiness levels have been demonstrated to correlate with objective physiological, medical and social characteristics such as unemployment, assessments of the person's happiness by friends, family members, and spouse, recollection of positive and negative life-events, authenticity of smiles, heart rate and blood pressure responses to stress and electroencephalogram measures of prefrontal brain activity (Blanchflower and Oswald, 2002; Frey and Stutzer, 2001; Bottan and Truglia, 2011). It appears well-being research scientists generally agree that subjective measures of well-being seem to validly measure well-being (as cited in Frey and Stutzer, 2001).

Policy Implications of Happiness Research

Happiness research may provide policymakers meaningful opportunities to extend the understanding of well-being beyond the economic factors that have been traditionally used. Well-being data can facilitate improved policy decisions, feedback, and potential for policy improvement. Rather than focusing on the policy goal of maximizing aggregate happiness and prescribing an agenda to individuals, happiness metrics could be used to improve the processes that citizens use to express their preferences (Graham, 2011). Thus, opportunities and education allow people the freedom to pursue happiness in accordance with their individual preferences.

To make a real difference in people's lives, decision makers have to consciously plan to incorporate well-being considerations into their policy choices. Over the last 10 years, policy interest in well-being has grown in line with academic research, with many countries actively developing well-being measures to use in public policy (Bhutan, the United Kingdom, France, Australia, New Zealand, Japan, Germany, Italy, and Canada). This cross-national momentum has continued to flourish since the 2011 United Nations General Assembly declaration that invited member states to "pursue the elaboration of additional measures that better capture the importance of the pursuit of happiness and well-being in development with a view to guiding their public policies" (New Economics Foundation, 2012). The current international interest in the new metrics of well-being is an opportunity to bridge the gap between well-being metrics and policy intervention. Figure 2.1 below summarizes the relationship between life satisfaction and national income around the world.

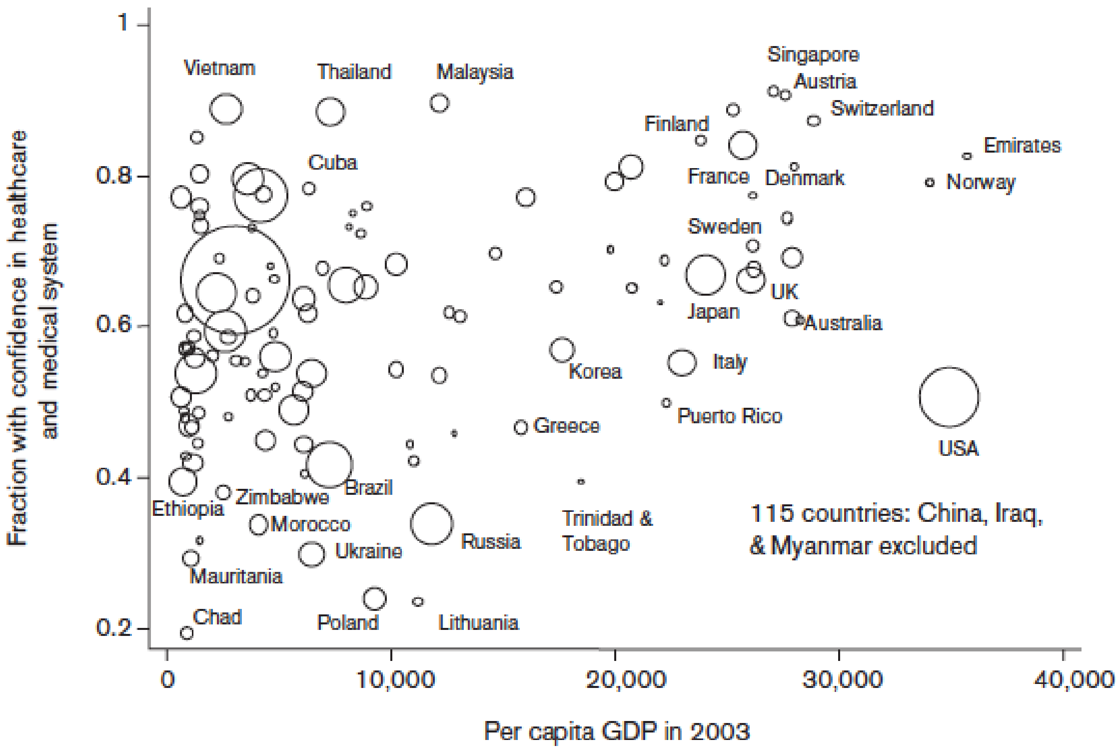
Figure 2.1: Life Satisfaction and Per Capita GDP around the World



Source: Deaton, 2008.
Note: Each circle is a country, with diameter proportional to population and marks average life satisfaction and GDP for that country. GDP per capita in 2003 is measured in purchasing power parity dollars at 2000 prices.

Figure 2.2 below shows the U.S. ranked 88th out of 120 in the World Poll in terms of confidence in healthcare and medical systems. Furthermore, in the World Health Organization, the U.S. ranked 37th out of 191 countries for its health system performance (Deaton, 2008).

Figure 2.2: Confidence in Healthcare and Medical Systems around the World



Source: Deaton, 2008.
Note: Each circle is a country, with diameter proportion to population.

Improved Tools & Data for Broader Measure of Well-being

Studies of happiness could provide government entities and policymakers better tools and data that extend beyond the income metrics that have been traditionally used. The research indicates that there are many other non-income predictors that can measure well-being, such as unemployment rates, health conditions, crime rates, commuting time, and environmental degradation (Graham, 2011). The expanded scope of happiness data would allow us to value non-income components and weight each component to compare how costs and benefits vary across countries and societies. When used with income measures, the extended data may provide a more accurate representation of societal well-being.

Informed Policy Decisions & Effect of Policies on General Welfare

A deeper understanding of well-being and happiness may better inform economic policy decisions or provide a broader and richer research foundation for policy strategy. When considering a budget cut, policymakers could make more informed choices by considering well-being impacts when choosing one policy or program over another. With extensive research on well-being, we can calculate how much income it would take to compensate a decline in life satisfaction occurring in the case of certain life events, such as divorce, death of a spouse, loss of a job, or a negative health condition. Likewise, researchers could calculate how much equivalent income a person would gain for boosted life satisfaction from positive events, such as marriage, increased quality of life, relief from chronic pain, sleep disorders, depression or increased education (Bok, 2010; Graham, 2011). There are pecuniary effects extending beyond income measures left unaccounted for if income factors are the only calculated measures. Moreover, well-being research could facilitate a quicker feedback process by enabling policymakers to track the effect of specific policies on the general welfare over time (Graham, 2011).

Deeper Understanding & Potential for Process Improvement

Well-being research may also provide a deeper understanding of individual well-being and its effects on communities and societies. This might allow us to better translate the effects of institutional condition, such as inequality, poverty, and quality of governance or environment on future policy initiatives. According to Bok (2010), an in-depth understanding of the threat of financial hardship such as insufficient retirement savings, risk of sickness without proper healthcare, or threat of losing a job can facilitate tremendous opportunities for reform to provide greater protection from financial risks causing suffering and anxiety among low and middle income American families.

Key Happiness Predictors

Throughout the world, people place significant importance on happiness. A survey of college students from 42 countries found 69% of respondents rated happiness at the top of the importance scale while 62% placed life satisfaction at the top of the importance scale (Diener, 2000). According to Graham's (2011) exhaustive research on happiness measurements around the world, standard happiness predictors in countries worldwide are remarkably stable and consistent, regardless of the countries' level of development. Socioeconomic and demographic determinants such as income, health, marriage, employment status, and economic stability are reliable and robust determinants of happiness and well-being. In this section, I describe the research and relevant theories on key happiness predictors.

Genetics and Personality

Although my study does not focus on the impact of personal characteristics such as genetics, personality traits, life outlook or predisposition, or cultural differences on individuals' level of happiness and life satisfaction, it is important to note that genetics and personalities are among the most consistent and robust predictors of well-being. This has been thoroughly established through studies of similarities in happiness among identical twins reared apart compared to those of non-identical twins who grew up together. The results show that identical twins reared apart are remarkably similar in their happiness level, while non-identical twins brought up together have very different happiness levels (Diener, 1999). The research indicates that some people have a genetic predisposition to be happy or unhappy, presumably caused by inborn individual differences in the nervous system. According to Wilson (1967), a happy individual is one who is extroverted, optimistic, and worry-free (as cited in Diener, et al., 1999). Diener (1999) also emphasizes that a happy person is "blessed with a positive temperament, tends to have a positive outlook, and does not ruminate excessively about bad events," in addition to living in an economically developed society, having social confidants, and possessing adequate resources to achieve set goals.

Personality traits exhibit some of the strongest correlations with SWB, with genes appearing to be partly responsible for these correlations. Lykken and Tellegen (1996) estimate this effect to be approximately 50% for immediate SWB and 80% for longer SWB. This translates to approximately 20 to 50% of the variance in long and short-term well-being (as cited in Kahneman, Diener, Schwarz, 1999). Furthermore, Tellegen estimates that genes account for 40% of the variance in positive emotionality and 55% of the variance in negative emotionality (as cited in Diener et al., 1999). Similarly, a report for the UK Prime Minister's Strategy Unit identified genetics and personality as two of the five factors shaping an individual's well-being, attributing 40 to 50% as being genetically determined (Walker & John, 2012). Although the literature provides ample evidence of the significance of genetics and personality traits on happiness, the regression model I develop in this study does not account for these effects since they are not available in the data set. Including these variables would potentially explain approximately 50% of well-being variance.

Income Effect

The prevalent discussion in well-being research gravitates toward the impact of income on individual happiness and life satisfaction. Traditionally, GDP of a country, which measures market value of all officially recognized goods and services produced within a country in a given period, is used as an indicator of residents' standard of living under the rationale that all residents would benefit from a country's increased economic production. According to Di Tella, MacCulloch, and Oswald (2002), macroeconomic movements have strong effects on the happiness of nations. Their research suggests that individual happiness is strongly correlated with movements in GDP. For example, recessions' effect on happiness is large as it is estimated that an equivalent of 3% of per capita GDP is needed to compensate for a typical U.S.-size recession (Di Tella, et al., 2002). Significant positive correlations were found between income and happiness as wealthy people, on average, report higher SWB and wealthier countries are happier than poorer countries (Stevenson and Wolfers, 2008; Blanchflower and Oswald, 2000; Gardner and Oswald, 2001; Easterlin, 1974; Frey and Stutzer, 2001; Graham, 2011; Graham, Eggers, and Sukhtankar, 2004).

Easterlin (1974) noted that while richer individuals are happier than poorer ones, over time U.S. residents did not become happier as they became richer, known as the Easterlin Paradox. Despite significant increases in real income, the average happiness level in the U.S. had remained largely flat. Furthermore, cross-country studies of happiness consistently demonstrate that after a certain minimum level of per capita income is reached, average happiness level does not increase as countries grow wealthier (Easterlin, 1974; Oswald, 1997). Similar conclusions were observed in studies conducted by Blanchflower and Oswald (2002) where despite increases in GDP, reported levels of happiness have been dropping in the U.S. and life satisfaction remained flat in the UK. This also suggests that relative income, rather than absolute income, matters more to well-being and happiness.

It appears that after a certain level of income where basic necessities are met, more money does not make people much happier (Graham, 2011; Graham et al., 2004). A study from Princeton University’s Woodrow Wilson School discovered that money could buy happiness, although it is capped at $75,000 a year (Luscombe, 2010). The lower a person’s income falls below this benchmark, the unhappier that person feels. On the other hand, those who earn more than $75,000 annually did not report any greater happiness (Luscombe). Researchers found that lower income did not necessarily cause more sadness, but rather being wealthier can ease the adversities that people face in life.

On the contrary, Stevenson and Wolfers (2008) reassessed the Easterlin Paradox with findings that suggest a link between society's economic progress and its average level of happiness. The researchers found that as countries become richer, people tend to become happier as well. This suggests that happiness within a country rises during periods of economic growth and rises most quickly when economic growth is most rapid. Fischer (2007) also disputed this paradox by asserting that per capita GDP is not a true measure of wealth as it has become increasingly, unevenly distributed. For example, in 2005 the top 20% of income recipients in the U.S. acquired 50% of the national income (Fischer, 2007). Fischer recalculated the same data using median household income, median male income, and mean hourly wages and found evidence that national happiness stalled because the average family had not been made better off financially during this time period (Fischer, 2007).

Walker & John (2012) also confirmed that well-being tends to be lower in countries with higher inequality in income and wealth. Specifically, Americans were found happier on average in years with less income inequality compared to years with more income inequality (Oishi et al., 2011, as cited in New Economics Foundation, 2012). Moreover, higher public spending and benefit entitlements appear to be associated with higher well-being at the national level.

Frey & Stutzer (2002a) found that those in the second highest income category reported a statistically significant 9.8 percentage points higher probability of being completely satisfied, compared to individuals in the lowest income category. The marginal income effect of individuals in the top category is only 7.4 percentage points higher than those in the lowest income category (Frey & Stutzer, 2002a). This suggests that highest income may not necessarily predict the highest percentage increase in happiness. In contrast, Salinas-Jimenez et al. (2010) found that the marginal income effect of individuals in the middle-income group is 17.6% higher and those in the rich income category is 21.2% higher than individuals in the low-income group. This result infers a significant relationship between income and life satisfaction, especially with increasing life satisfaction as individuals move from the lowest to the highest income group.

Researchers also found an inverse effect between income and happiness. For example, Graham et al. (2003) found that residual happiness was associated with higher levels of income in future periods, controlling for income, education, and other socio-demographic variables. The comparison of a large panel dataset from Russia on happiness levels between 1995 and 2000 indicated that people with higher levels of happiness are more likely to increase their own income in the future and that happiness was motivated more by future income for those with less income. Specifically, they found that a one-point increase in unexplained or residual happiness in 1995 yielded a three percent increase in income in 2000 (Graham et al., 2003). This suggests the relationship between happiness and income can be both cause and effect since higher income is predicted to increase happiness while increased happiness can also result in earning higher future income.

Unemployment

Multiple studies indicate that GDP and income may not be the best predictors of well-being and therefore need to be supplemented with other measures to assess individual and societal well-being. Studies consistently found a substantial influence of non-financial variables on self-reported satisfaction and that non-income factors accounted for more variance in happiness than income factors (Headey and Wooden, 2004; Frey and Stutzer, 2001; Sharpe, Ghanghro, and Johnson, 2010, Bottan and Truglia, 2011). For example, the unemployed were generally found to have a 5 to 15% lower score on self-reported happiness compared to those who were employed (Di Tella et al., 2002; Frey & Stutzer, 2001, 2002; New Economics Foundation, 2012). The effect of unemployment was associated with highly significant lower levels of happiness since individuals typically required approximately two years to adapt to 72% of their prior happiness levels (Bottan and Truglia, 2011).

More importantly, the effect of unemployment held above and beyond the effects of forgone income (Bok, 2010; Blanchflower and Oswald, 2002). Unemployment seems to have serious implications for individuals, as joblessness was associated with a significant rise in anxiety, depression, loss of confidence and self-esteem. For example, the odds of someone considering himself or herself worthless were 2.88 times higher for unemployed individuals, but only 1.44 times greater for those out of the labor market, and 1.26 times greater for low-paid individuals (Theodossiou, 1997). Furthermore, unemployed individuals were found to have 2.56 times greater odds of reporting lower levels of general happiness compared to individuals in the higher-paying segment of the labor market (Theodossiou, 1997). Overall, well-being research consistently found that employment status greatly influenced individual well-being.

Marriage and Family

Marriage is highly correlated with increased happiness. According to Blanchflower and Oswald (2002), marriage is worth $100,000 per year compared to being widowed or separated. Clark and Oswald (2002) found that it would take, on average, an extra $267,000 per year to offset the degree of unhappiness of widowhood. Similarly, Frey and Stutzer (2002) reported that the proportions of people reporting the highest happiness scores who had no partner and were separated, widowed, or divorced were 15.9, 6.5, and 10.9 percentage points lower, respectively than for married individuals.

Layard (2005) found that marriage is the second most important factor that affects individual happiness. According to Layard's research, married people are happier than those who are divorced, separated, widowed, or never have been married (2005). Stack and Eshleman's study revealed that marriage was 3.4 times more closely tied to the variance in happiness than cohabitation, and that marriage increased happiness equally for both men and women (1998). Furthermore, their research indicated that the positive relationship between marital status and happiness held constant in 16 of the 17 nations studied, with the strength of the association not varying significantly in 14 of the 17 nations. Additionally, the odds of a single individual reporting a lower ability to enjoy normal day-to-day activities are 0.76 times lower and the odds of divorced individuals at a lower level of general happiness are 1.19 times greater, compared to their married counterparts (Theodossiou, 1998).

Besides the effects of marriage, researchers consistently found that children appear to be a source of stress for parents, which can lead to lower general happiness. With each additional dependent child, the odds of a parent reporting a higher level of psychological strain and greater loss of confidence increased by 1.1 times (Theodossiou). Furthermore, the odds of being in a lower level of general happiness and feeling less able to face problems increased by 1.11 and 1.06 times, respectively, with each additional dependent child (Theodossiou, 1998).

Health Effect

In general, there is robust evidence suggesting that physical and mental healths are among the strongest predictors of well-being and life satisfaction. Most regression-based studies found that self-reported health status has the highest or next to highest impact on life satisfaction, next to income, marital and employment status, thus heightening the prominent role of health on well-being. The effect of health on SWB remains substantial even after controlling for the reverse impact that SWB has on health. Moreover, longitudinal studies continue to show a strong effect of health on well-being (Dolan et al., 2008, as cited in New Economics Foundation, 2012). Regression-based studies on the effect of health are discussed in detail in the following section.

Health Effect on Happiness and Well-Being

In many studies, health is measured subjectively in that respondents are asked to rate their own health rather than relying on physicians' observations or biological measures of morbidity. Although poor objective health is associated with lower well-being, this relationship is weaker than that of self-reported health. Objective health and happiness have a weaker relationship because self-rated health measures reflect not only an individual's actual physical condition but also one's level of emotional adjustment (Diener, et al., 1999). Therefore, perceptions of health have a higher impact on SWB.

Okun et al. (1984)'s meta-analysis of 104 studies concluded that objective and subjective measures of health accounted for 8 to 14% of the variance in SWB (Sirgy, 2012). Compared to individuals with poor health, the Earth Institute (2012) found excellent health increased an individual's life satisfaction score by 3.45 points while good health improved the score by 2.82 points on a 10-point scale. Similarly, Salinas-Jimenez et al. (2010) detected the significant role of health on life satisfaction, with very good health, good health, and fair health increasing life satisfaction by 1.62, 1.09, 0.64 points on a 10-point scale, respectively. Those with poor or fair self-rated health were 4.16 times more likely than those with better self-rated health to fall in the lower quartile of happiness, with health being the highest happiness predictor next to health literacy and college education (Angner, et al., 2009). Furthermore, the monetary value of compensation for poor health tends to be high, up to $128,000 or approximately 60 to 1,000% of an individual's mean income (Mello & Tiongson, 2009). This finding is consistent with standard estimates of the statistical value of a life-year in perfect health, which is between $90,000 and $420,000 in 2000 prices (Tolley et al., 1994, as cited in Mello & Tiongson). Moreover, Sharpe et al. (2010) found a one-unit increase in health status on happiness is equivalent to a 155% increase in household income. Overall, 60% of the explained variance in happiness scores was attributable to health satisfaction (George & Landerman, 1984; Larsen, 1978; Michalos et al., 2007; as cited in Sirgy, 2012).

According the International Labour Organisation, the costs of mental ill health represent three to four percent of the European Union's GDP (Laplane, 2013). At any moment, about 20% of the working-age population within the OECD suffers from a mental disorder with depression, anxiety, and substance-use disorders among the most common (Laplane). Half of those who are mentally ill as adults were already ill by age 15. These individuals are more likely to have experienced low earnings, unemployment, criminal records, teenage pregnancy, physical illness, and poor educational performance (Earth Institute, 2012). A recent World Health Organization report found that depression was 50% more disabling than chronic physical illness such as angina, asthma, arthritis or diabetes, with mental illness accounting for 43% of disabilities in advanced countries and 31% of disabilities world-wide, 26% of the burden of disease in advanced countries and 13% world-wide (Earth Institute, 2012). Although the majority of mental illness, such as depression and anxiety, is treatable with significant benefits, only a quarter of people with mental illness receive treatment, compared to over three quarters of those with physical conditions (Earth Institute).

One important conduit through which genes operate is mental health. Psychological health has a very strong relationship with SWB and seems to be more highly correlated with well-being than physical health. Sharpe et al. (2010) indicated that mental health status, physical health, stress level, and a sense of belonging to the local community have a statistically greater impact on happiness than economic factors. They found that a one-unit increase in mental health on happiness was equivalent to the effect of a 209% increase in household income or a 17.5 percentage point increase in life satisfaction. Furthermore, a one-unit increase in stress level was equal to the effect of a 140% decrease in household income with respect to happiness. In another study, mental health was found to account for a 0.292 point decrease in happiness (Mello, 2009). Similarly, Abdel-Khalek (2006) reported results from a multiple regression analysis in which self-rated mental health accounted for 60% of the variance in predicting happiness. Depression, anxiety, bipolar disorder, and schizophrenia were associated with a significantly lower well-being level (Diener & Seligman, 2004; Packer et al., 1997, Koivumaa-Honkanen et al., 1999; Arnold et al., 2000, Suslow et al., 2003; Bradshaw and Brekke, 1999, as cited in New Economics Foundation, 2012). Furthermore, Bok (2010) found chronic pain, sleep disorder, and depression among the severe afflictions affecting a large segment of the population and thus believed treatment of these illnesses should be the top priorities of any government seeking to improve the general public's well-being (Bok, 2010).

Disability status also negatively affected individual well-being, even though there is evidence that individuals adapt somewhat to their disability status. Dolan et al. (2008) found that disability reduces life satisfaction by 0.596 points on a one to seven scale for individuals with no past disability, 0.521 points after one year of disability, 0.447 points after two years, and 0.372 points after three years. Similarly, other studies found the impact of severe disability at 0.6 points and the impact of moderate disability at 0.4 points, on a one to seven life satisfaction scale (Earth Institute, 2012). Adaptation to disability is estimated at around 50% for a moderate disability and 30% for a severe disability, with approximately one-third of the life satisfaction effect of a severe disability dissipating over time (Earth Institute, 2012). The impact of an individual's health depends on his or her perception of the situation. When a disabling condition is severe or entails multiple or chronic problems, it may negatively influence SWB. Evidence suggested that although people may adapt somewhat to chronic illness, complete adaptation does not usually happen.

Whether health status causes happiness or happiness causes self-reported health status is an ongoing discussion. There is evidence of the reverse impact of happiness on health with more happiness predicting better future physical health. For example, there is a high correlation between low well-being scores and subsequent coronary heart disease, strokes, suicide, and shorter lifespan (Earth Institute). Furthermore, there is evidence of an inverse relationship between national SWB and national blood-pressure problems, with happier nations reporting fewer blood-pressure problems (Blanchflower et al., 2007). Although most researchers recognize that the causal link between health and SWB is controversial, they tend to view well-being mainly as an effect, rather than a cause in the relationship. This is evidenced as the effect of health on SWB remains substantial even after controlling for the reverse impact that SWB has on health (Diener et al., 1999; Shields & Wheatley Price, 2005, as cited in Dolan et al., 2008).

Gap in Happiness and Well-Being Literature

Although considerable regression-based research focused on the substantial effects of health on SWB, minimal attention was paid to the effect of health insurance coverage and health care cost on well-being. With over 48 million Americans lacking health insurance coverage (more than one in six uninsured non-elderly individuals) and given the ACA's goal to reduce this uninsured percentage, studying the impact of health insurance coverage on well-being can help us assess the magnitude of the ACA's impact on Americans' well-being. While there are tremendous known economic impacts of this health care legislation, the need to understand its impact on individual well-being is also important.

To date, there is only one discussion paper written on the relationship between happiness and health care coverage. In this paper, Blanchflower (2009) studied the impact on happiness of not being able to see a doctor due to cost. Blanchflower found the effect of not being able to see a doctor due to cost was extremely substantial and significant, at a 21-percentage point decrease in happiness. The magnitude of this effect was approximately the same as the difference in happiness variance between having zero income and income of greater than $75,000 or between being employed and having been unemployed for at least twelve months (Blanchflower, 2009).

A health insurance experiment in Oregon that randomly selected uninsured low-income adults to provide them health insurance coverage found that those in the treatment group (receiving access to health care) had higher health care utilization, lower-out-of-pocket medical expenditures and medical debt and better self-reported physical and mental health than those not in the treatment group (Finkelstein et al., 2011). Similarly, a separate study of New York, Maine and Arizona found that the expansion of Medicaid eligibility for adults was associated with reduced mortality and improved access to care and self-reported health status (Kaiser Family Foundation, 2012b). Since the lack of health insurance can reduce access to timely health care, lack of health insurance is linked to delayed care, costly urgent or emergency treatment, unmet health care needs, anxiety and stress, poorer overall health, disability, and premature death (Lee & McConville, 2011). Studies are demonstrating that gaining health insurance coverage considerably restores access to health care and diminishes the adverse effects of having been uninsured. Furthermore, there is evidence that when adults acquire health insurance, many of the negative health effects of the lack of health insurance are mitigated (Institute of Medicine, 2009). Moreover, health insurance coverage adds value beyond its relationship to access to health care, such as improved physical and mental health and a mitigated state of anxiety that many uninsured participants recalled as endemic to living without coverage.

Overall, lack of health insurance coverage contributes greatly to poorer physical and mental health, which implies that it may potentially have a strong negative effect on happiness and well-being. This study will bridge the gap in happiness and well-being literature by analyzing the effect of health insurance coverage and health care cost on well-being. Understanding this connection will help us understand the effect of the ACA on happiness and well-being and the value of health coverage expansion on the lives of individuals. If results from this study align with Blanchflower's (2009) study, it could help validate increased government spending toward health coverage expansion to help the U.S. bridge the health care access equity gap in our health care system and improve well-being. Studies from states that offer near universal health care show benefits far exceeded the costs of health care expansion, and that extending health insurance coverage to the uninsured can reverse many of the detrimental health effects due to the lack of health insurance. Potentially, this study could help strengthen policy decisions to increase health care access and improve the lives of uninsured Americans.

Chapter Three

METHODOLOGY

The literature reviewed in the previous chapter captures some of the different characteristics associated with happiness and well-being. Although there are specific key attributes noted, such as personality and genetics, income, health, unemployment, and marital status, there may be infinite other factors that could impact individual well-being. How is it then possible to test the hypothesis of this thesis, that individuals with health insurance coverage and those residing in states with more generous Medicaid benefits are more likely to be happy than those without health insurance coverage and those living in states with less generous Medicaid benefits? To determine the causal effect in my hypothesis, I use regression analysis, a statistical tool for the investigation of relationships among variables, to estimate the quantitative effect of the causal variables: health insurance coverage, health care cost, and Medicaid factors upon the happiness variable. This technique has long been central to the field of economics as well as other social sciences, and is widely used in policy analysis to explain movements in one variable, the dependent variable, as a function of movements in a set of other variables, the independent or explanatory variable (Studenmund, 2011). Regression analysis holds constant major characteristics discussed in the literature review thought to cause happiness to determine the impact of health insurance coverage and Medicaid generosity on happiness.

This chapter provides a description of the statistical methodology and data set used in the equation to evaluate the impact of health insurance coverage on happiness and well-being. The first section describes the data used to conduct this analysis. The following section explains the theory for the regression model construction, the rationale for the variables included in the model, and my hypotheses about the effect of each variable within the given population.

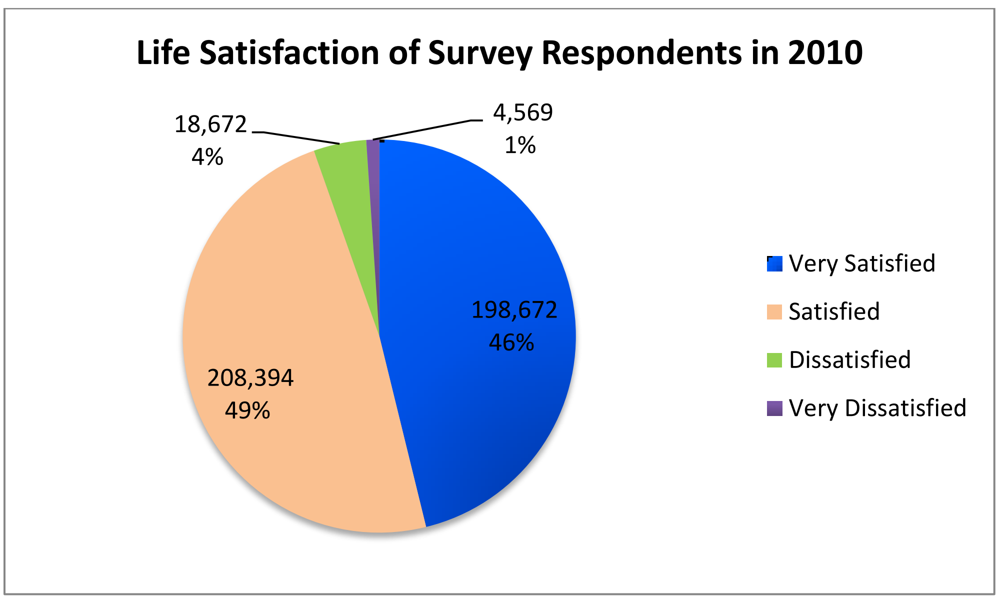
Data Collection

The data for this study come from the Centers for Disease Control and Prevention (CDC)'s Behavioral Risk Factor Surveillance System (BRFSS) 2010 survey. Established in 1984, the BRFSS is an ongoing data collection program designed to measure behavioral risk factors in adult population living in households, such as information pertaining to health risk behaviors, preventive health practices, and health care access (CDC, 2010). The BRFSS contains uniform, state-specific data on preventive health practices and risk behaviors that are linked to chronic diseases, injuries, and preventable infectious diseases affecting the adult population. Data are collected from a random sample of adults through a telephone survey and are used to identify emerging health problems, establish and track health objectives, and develop and evaluate public health policies and programs. To date, the BRFSS houses the world's largest on-going telephone health survey system with over 350,000 adults interviewed each year (CDC, 2010). Based on the literature review on happiness and well-being research, the broad causal factors contributing to the level of happiness are demographics, family situation, education, economics, and health. As discussed in the literature review, my model does not include genetics and personality factors among the selected well-being determinants since they are not available in the data set.

The dependent variable in my regression model is participants' life satisfaction, which is measured by a single item with fixed response categories. Respondents in the BRFSS were asked, "in general, how satisfied are you with your life—very satisfied, satisfied, dissatisfied, very dissatisfied" (CDC, 2010). Life satisfaction is defined on a scale between 1 and 4, with 1 being very satisfied, 2 equaling satisfied, 3 being dissatisfied, and 4 equaling very dissatisfied. In my regression analysis, I recoded the happiness scale so that one represents being very satisfied or satisfied with life, while zero equals being dissatisfied or very dissatisfied with life.

The data indicates that 46% of respondents are very satisfied with their life, 49% are satisfied, 4% are dissatisfied, and one percent is very dissatisfied (see Figure 3.1 below). This is consistent with findings in well-being literature as most people report being satisfied or very satisfied with their life. According to Frey and Stutzer (2002a), most people in the U.S. indicated that they are reasonably happy, with 20% of respondents considering themselves to be very happy, and no less than 62% reported satisfaction scores above seven on a 10-point scale. Very few people reported being dissatisfied, with only five percent placing themselves in the lowest three categories. On average, Americans had a life satisfaction score of 7.67 on a 10-point scale (Frey & Stutzer, 2002a).

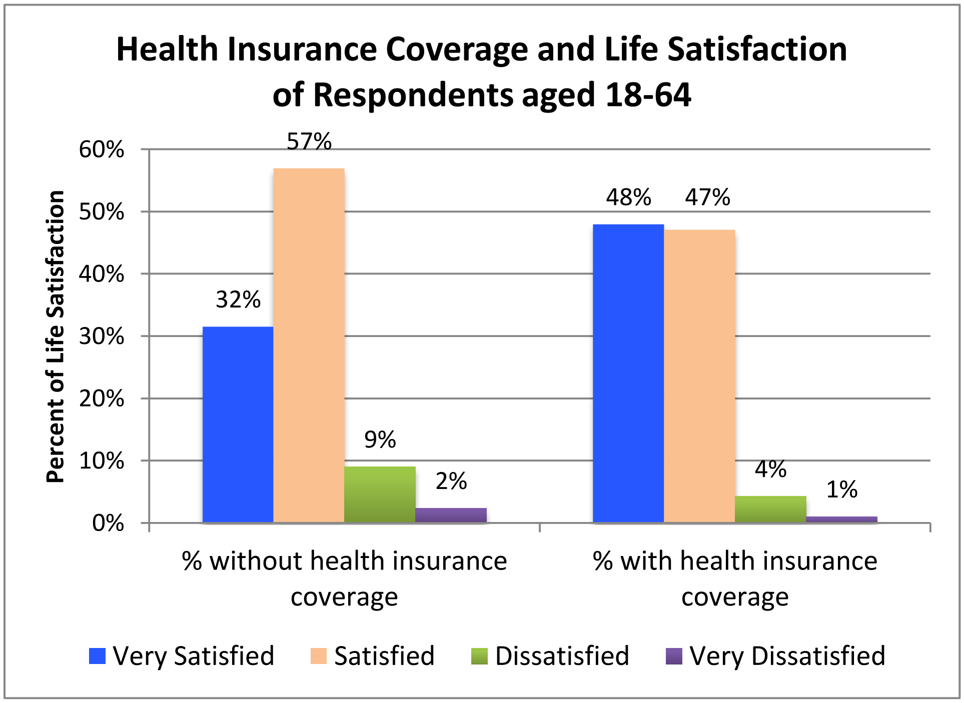
Figure 3.1: Frequency Distribution of Survey Respondents' Life Satisfaction, 2010



Source: 2010 BRFSS Survey, CDC, 2010.

Figure 3.2 below provides the percentage of life satisfaction for individuals aged 18 to 64 with and without health insurance coverage in the 2010 BRFSS survey. The data suggests on average, respondents without health insurance coverage are less likely to be satisfied with their life and more likely to be dissatisfied with their life (CDC, 2010). Compared to respondents with health insurance coverage, respondents aged 18 to 64 without health care coverage are 16-percentage points less likely to be very satisfied, 10-percentage points more likely to be satisfied, five-percentage points more likely to be dissatisfied, and one-percentage point more likely to be very dissatisfied with their life.

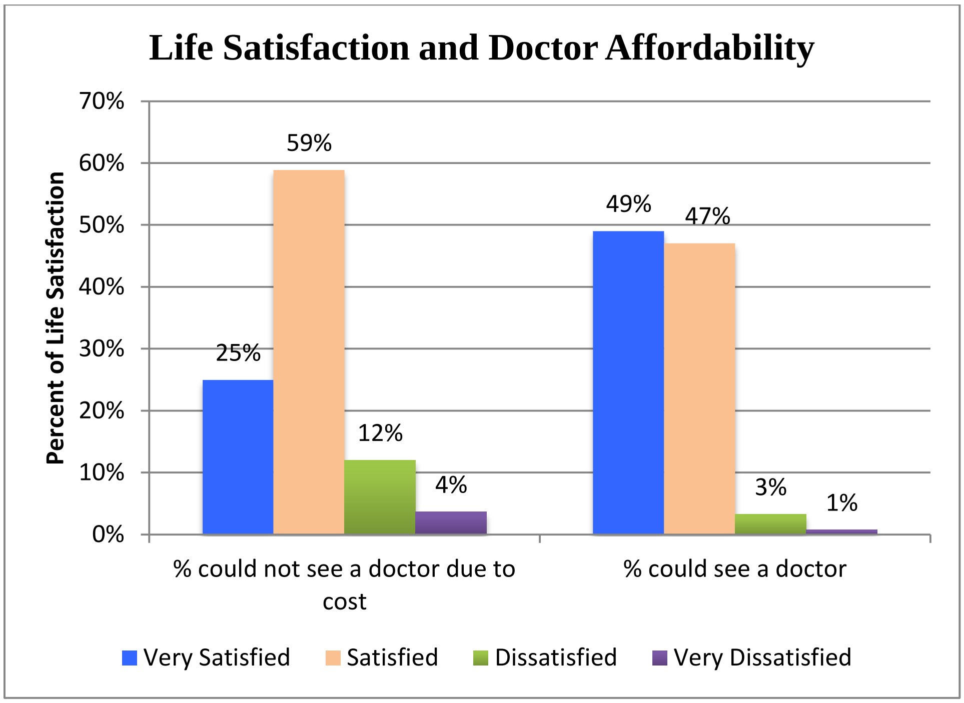
Figure 3.2: Health Insurance Coverage and Life Satisfaction of Respondents Aged 18-64, 2010



Source: 2010 BRFSS Survey, CDC, 2010.

Figure 3.3 below provides the percentage of life satisfaction for individuals who could and could not see a doctor due to cost from the 2010 BRFSS survey. The data suggests on average, respondents who could not afford to see a doctor are less likely to be satisfied with their life and more likely to be dissatisfied with their life (CDC, 2010). Compared to respondents who could afford a doctor, respondents who could not see a doctor due to cost are 24-percentage points less likely to be very satisfied, 12-percentage points more likely to satisfied, nine-percentage points more likely to be dissatisfied, and three-percentage points more likely to be very dissatisfied with their life.

Figure 3.3: Life Satisfaction and Doctor Affordability, 2010



Source: 2010 BRFSS Survey, CDC, 2010.

In addition to the BRFSS data set, I include data on states' Medicaid rankings to assess whether higher levels of well-being are observed in states with more generous Medicaid rankings. This data comes from a 2007 report published by the Public Citizen Health Research Group, which measured 55 assessment indicators across four Medicaid evaluation categories: eligibility, scope of services, quality of care, and reimbursement (Ramírez de Arellano & Wolfe, 2007). One hundred points are distributed among these categories, with relative weights as follows: eligibility (0.35), scope of services (0.20), quality of care (0.20), and reimbursement (0.25). The overall score for each state is the sum of the scores for all four categories.

Given changes in programmatic mandates, there are great disparities in Medicaid programs across states and even greater differences within states since states have considerable latitude in how they run their Medicaid programs. The result indicates the top ten Medicaid ranking states clustering in the Northeast, listed in descending order as follow: Massachusetts, Nebraska, Vermont, Alaska, Wisconsin, Rhode Island, Minnesota, New York, Washington, and New Hampshire (Ramírez de Arellano & Wolfe, 2007). The worst ten states in descending order are: Mississippi, Idaho, Texas, Oklahoma, South Dakota, Indiana, South Carolina, Colorado, Alabama, and Missouri. A listing of scores by category indicates extreme disparities among states, with scores varying by 2.5-fold for scope of services, more than three-fold for eligibility, greater than 17-fold in quality of care, and more than 20-fold in reimbursement (Ramírez de Arellano & Wolfe, 2007). Score and rankings for each of the four categories are displayed in Table 3.1 below, including the overall score and ranking for each state.

Table 3.1: Scores and Ranks for State Medicaid Programs by State

	Eligibility		Scope of Services		Quality of Care		Reimbursement		Overall	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank*	Score	Rank*
Alabama	91.6	50	71.9	49	97.1	7	115.7	25	376.3	42
Alaska	159.3	33	105.1	33	95.5	8	250.0	1	609.9	4
Arizona	95.5	48	142.5	8	52.5	30	184.2	4	474.5	24
Arkansas	190.0	23	94.4	43	19.5	45	111.7	26	415.7	38
California	258.9	5	141.0	10	50.4	33	75.4	42	525.7	14
Colorado	131.8	41	100.6	40	22.4	42	120.9	21	375.7	43
Connecticut	218.7	14	98.9	42	43.7	36	144.6	10	505.8	19
Delaware	127.1	43	86.2	45	63.1	23	200.4	2	476.8	22
District of Columbia	248.5	7	116.3	27	29.4	41	68.8	45	462.9	27
Florida	182.4	27	103.5	35	106.4	4	75.4	42	467.7	26
Georgia	190.9	22	76.3	48	22.4	42	136.5	15	426.1	36
Hawaii	245.0	10	135.1	16	66.7	22	100.2	30	547.1	11
Idaho	117.1	44	91.6	44	-4.4	51	120.9	21	325.2	49
Illinois	143.6	36	145.1	5	71.4	16	79.5	39	439.6	32
Indiana	90.6	51	111.6	31	71.4	16	83.5	37	357.2	45
Iowa	186.0	25	120.7	25	43.4	37	160.1	6	510.2	17
Kansas	183.0	26	131.2	19	18.0	47	100.2	30	432.4	35
Kentucky	162.8	30	104.8	34	105.1	6	123.9	20	496.6	20
Louisiana	228.7	11	118.2	26	10.2	48	100.2	30	457.3	28
Maine	210.0	18	142.6	7	92.7	10	83.1	38	528.4	13
Maryland	226.4	12	125.4	23	18.8	46	152.7	8	523.3	15
Massachusetts	247.6	8	138.5	12	143.0	1	116.9	23	645.9	1
Michigan	217.0	15	124.3	24	55.1	27	79.5	39	475.8	23
Minnesota	254.5	6	158.1	2	50.7	32	127.9	19	591.2	7
Mississippi	92.6	49	66.8	51	58.2	25	100.2	30	317.8	50
Missouri	141.8	37	102.1	39	68.3	20	66.9	47	379.1	41
Montana	159.7	32	135.8	15	72.4	15	144.6	10	512.5	16
Nebraska	220.1	13	138.8	11	105.4	5	161.3	5	625.5	2
Nevada	108.5	46	102.8	36	8.4	49	185.3	3	405.0	40
New Hampshire	211.3	17	136.8	13	84.4	12	116.5	24	548.9	10
New Jersey	216.8	16	126.6	22	55.1	27	12.2	50	410.7	39
New Mexico	160.1	31	113.6	29	32.8	39	140.5	12	447.0	30
New York	264.8	3	168.3	1	83.1	13	44.0	49	560.2	8
North Carolina	188.9	24	108.2	32	69.1	19	140.5	12	506.6	18
North Dakota	139.8	38	145.1	5	53.9	29	104.3	29	443.2	31
Ohio	144.9	35	112.5	30	106.7	3	87.6	36	451.7	29
Oklahoma	193.3	21	71.7	50	-3.8	50	75.4	42	336.7	47
Oregon	204.9	19	155.0	3	51.7	31	132.4	17	544.0	12
Pennsylvania	198.3	20	115.1	28	56.4	26	68.0	46	437.8	33
Rhode Island	296.8	1	134.7	17	109.0	2	59.5	48	600.0	6
South Carolina	132.7	40	82.9	46	20.1	44	128.3	18	364.0	44
South Dakota	101.1	47	102.5	37	37.7	38	111.3	28	352.6	46
Tennessee	175.2	28	141.6	9	85.7	11	NA*	NA*	NA*	NA*
Texas	110.3	45	100.3	41	45.5	35	79.5	39	335.5	48
Utah	167.4	29	132.8	18	80.5	14	100.2	30	480.9	21
Vermont	283.7	2	128.2	21	67.8	21	136.5	15	616.1	3
Virginia	131.0	42	102.4	38	94.0	9	96.1	35	423.5	37
Washington	260.9	4	145.8	4	31.7	40	111.7	26	550.0	9
West Virginia	157.5	34	128.4	20	48.1	34	140.5	12	474.4	25
Wisconsin	246.6	9	136.7	14	71.4	16	152.0	9	606.8	5
Wyoming	133.7	39	81.9	47	62.1	24	160.1	6	437.8	33
Total Possible	350.0		200.0		200.0		250.0		1000.0	

Source: Ramírez de Arellano & Wolfe, 2007.

Regression Model

A regression model attempts to specify cause and effect relationships between a dependent variable and explanatory variables. To conduct a regression analysis, I build a model informed through research and the literature to estimate the relationship between the dependent and independent variables used in the analysis. Thus, existing literature provides a theoretical basis for creating a regression equation to explain the impact of various factors such as health insurance coverage, health care cost, and Medicaid rankings on life satisfaction.

The model represented as an equation is as follows:

Life Satisfaction level = *ƒ* [Demographics, Family Situation, Education, Economics, Health, Key Explanatory Variables]

Explanatory and reference variables are specified in the function below and are described in detail in the following section (Table 3.2). Justification for these variables and their expected signs follow this model.

Demographic = *ƒ* [Race*: African American, Asian, Native Hawaiian, American Indian, Other Race, Multi Racial, Hispanic; Age; Female]
*the reference group for Race is White

Family Situation = *ƒ* [Marital Status*: Married, Divorced, Widowed, Separated, Unmarried Couple; Children]
*the reference group for Marital Status is Never Married

Education = *ƒ* [Years in School*: Grades 1-8, Grades 9-11, High School Graduate, 1-3 Years College, College Graduate]
*the reference group for Years in School is Never Attended School

Economics = *ƒ* [Household Income*: less than $10k, $10k to less than $15k, $15k to less than $20k, $20k to less than $25k, $25k to less than $35k, $35k to less than $50k; Employment Status*: Self-employed, Unemployed for more than 1 year, Unemployed for less than 1 year, Homemaker, Student, Retired, Unable to Work]
*the reference group for Household Income is Income greater than $75k; the reference group for Employment Status is Employed.

Health = *ƒ* [Health Status*: Excellent Health, Very Good Health, Fair Health; # of Days with Poor Physical Health in 1 Month; # of Days with Poor Mental Health in 1 Month; # of days with not Enough Sleep in 1 Month] *the reference for Health Status is Poor Health

Key Explanatory Variables = *f* [No Health Insurance Coverage; Cannot Afford a Doctor; State Specific Medicaid Rankings in the Areas of: Eligibility, Scope of Services, Quality of Care, Reimbursement]

Causal Model Justification

Before running a regression analysis, it is important to estimate what results might occur from the analysis based on theoretical reasoning and findings from the literature review. This provides a baseline for comparing results. Following is the rationale for the choice of the specific attributes and their predicted effect on well-being.

Demographics

Included in this function are individual characteristics such as race, age, and gender. Prior research suggests that ethnic differences may have varying influence on overall happiness level. Since studies indicate that African Americans are generally less happy compared to their white counterparts, my expected sign for African American is negative as my comparison group is white (Dolan et al., 2006; Lee and Bulanda, 2005; Magdol, 2002; Thoits and Hewitt, 2001, as cited in New Economics Foundation, 2012). I did not come across happiness predictions for the remaining races and therefore, placed a question mark for the expected sign for other ethnic variables. Prior research indicated that the relationship between age and happiness was U-shaped, with young and old people reported being happier than middle-aged people and the least happy people aged between 30 and 35 (Frey and Stutzer, 2002b; New Economics Foundation, 2012). In most advanced countries, women reported higher satisfaction and happiness than men (Earth Institute, 2012). Thus, I would expect a positive sign for the female variable.

Family Situation

Evidence consistently indicated that marriage is an important factor in statistical analyses regressing overall happiness on a set of explanatory variables (Earth Institute, 2012; New Economics Foundation, 2012; Blanchflower and Oswald, 2002; Clark and Oswald, 2002, Frey and Stutzer, 2002; Layard, 2005; Stack and Eshleman, 1998; Theodossiou, 1998). Married individuals are found to be happier than those who are never married, widowed, divorced, or separated. As a result, I place a positive sign expectation for those who were married relative to the excluded group, those who were never married. I also place a question mark next to widowed, divorced, and separated individuals. Since individuals who have children were predicted to be less happy due to the stress of parenting, I expect a negative sign for this group (Theodossiou, 1998; New Economics Foundation, 2012).

Education

Although the education variables are not key predictors of happiness, there is enough evidence indicating that schooling has some influence on happiness to prompt me to add years of education as a control variable. Many studies have found that educated individuals tend to be happier when controlling for other factors such as income and health (New Economics Foundation, 2012; Frey and Stutzer, 2002b). Furthermore, positive relationships between education and well-being were found. As a result, I expect the signs to be positive for individuals with more years of education, since never having attended school is the excluded category in my regression model.

Economics

Economic variables are critical factors to include in my regression analysis as the debate on well-being often centers on the impact of income and other economic factors. As discussed in the literature review section, income is one of the key predictors of happiness (De Tella, MacCulloch, and Oswald, 2002; Stevenson and Wolfers, 2008; Blanchflower and Oswald, 2000; Gardner and Oswald, 2001; Easterlin, 1974; Frey and Stutzer, 2001; Graham, 2011; Graham, Eggers, and Sukhtankar, 2004). Thus, compared to individuals in the highest income group, individuals in lower income groups are expected to have negative signs. Since relative income matters, I also include other factors related to income, such as employment status and hours worked weekly. With evidence of unemployment's significant negative effect on happiness, I expect a negative sign for unemployment status even after controlling for income, with the impact being more dramatic for individuals who are unemployed for more than 12 months (Blanchflower and Olswald, 2002; Theodosiou, 1997; Headey and Wooden, 2004; Frey and Stuzer, 2001; Sharpe, Ghanghro, and Johnson, 2010, Bottan and Truglia, 2011). Similar to age, I expect that the hours worked weekly may have a U-shaped relationship with happiness, as increased work hours can bring greater financial security and personal fulfillment, while working too many hours could impose detrimental opportunity costs, such as having less time to spend with family and leisure activities.

Health

Again, many studies found self-reported physical and mental health to be among the key happiness predictors (Okun et al., 1984; Angner, et al., 2009; Mello and Tiongson, 2009; Sirgy, 2012; Abdel-Khalek, 2006; New Economics Foundation, 2012). Nevertheless, these measurements may not be a true representation of the individual's health status, as they are based solely on subjective self-evaluations. Health status may be subject to fluctuations in participants' current state of mind and mood at the time of survey participation. Poor health status, such as experiencing a high level of pain, increased depression, or lack of sleep, have the potential to heavily influence the individual's state of happiness. As Bok (2010) pointed out, depression, lack of sleep, and pain is strongly associated with happiness level, therefore I included a measure of physical and mental health in this portion of my regression model. I expect positive signs for positive physical and mental health status compared to individuals with poor physical and mental health status.

Key Explanatory Variables

This study focuses specifically on the impact of health insurance on happiness. Accordingly, I included a variety of health insurance coverage variables in my statistical analysis, among which were the presence of health insurance coverage, whether an individual can afford to see a doctor, and states' Medicaid rankings on program eligibility, scope of services, quality of care, and reimbursement. I hypothesize that there is a negative impact on well-being for individuals without health insurance coverage and those who cannot afford to see a doctor because of cost, and a positive effect on individuals' happiness for those living in states with higher Medicaid rankings.

Data Sample

The data set analyzed in this study includes the BRFSS 2010 survey collected by the CDC, which included 451,075 observations. After dropping missing observations, the data sample used for the full regression consisted of 340,580 observations. The following two tables (Table 3.2 and 3.3) provide summary information of the explanatory variables and their associated statistics. Table 3.2 below provides a description of each of the variables used in the regression model and expected impact these variables will have on the dependent variable. In this table, a "+" sign indicates that the variable is expected to have a positive predictor effect on the dependent variable, a "-" sign indicates a negative predictor effect, a "+/-" sign is a mixed nonzero effect indicating that the variable could predict either way, and a "?" sign indicates an unknown effect.

Table 3.2: Variable Labels, Expected Impact, Description, and Sources

Variable Name	**Expected Impact**	**Description**
Life Satisfaction (dependent)	Dependent variable	General life satisfaction, specified as 1 = "very satisfied" or "satisfied", 0 = "very dissatisfied" or "dissatisfied."
KEY EXPLANATORY VARIABLES		
No Health Insurance Coverage	-	Equals 1 if respondent reports not having health insurance coverage; else equals 0
Cannot Afford Doctor	-	Equals 1 if respondent reports not being able to see a doctor when needed; else equals 0
Percent Medicaid Eligibility for State*	+	Percent of states' Medicaid eligibility score from total possible score. Score assigned using criteria such as age, income, citizenship status, assets, work status, marital status, enrollment in school, medical condition, improvement potential, etc. States with more generous eligibility criteria have higher score.
Percent Medicaid Scope of Services for State*	+	Percent of states' Medicaid scope of services score from total possible score. Score assigned based on criteria on coverage (states offering an optional service), population covered (extent of services to the medically needy as well as categorically needy), comprehensiveness (wide scope of services – amount, frequency and duration), lack of financial barrier (services that do not depend on cost-sharing, nominal fee that is unlikely to deter access to services vs. significant fee that may be a barrier to prompt care). States with more generous scope of services are scored higher in this category.
Percent Medicaid Quality of Care for State*	+	Percent of states' Medicaid quality of care score from total possible score. Score assigned based on indicators such as structure (elements that facilitate or promote quality of care), process (whether proper procedures were used in delivering care), and outcomes (improvements in health status and the avoidance of adverse results). States with higher quality of care scored higher in this category. Two states, Oklahoma and Idaho, fall short of the acceptable minimum standards, were given negative points.
Percent Medicaid Reimbursement for State*	+	Percent of states' Medicaid reimbursement score from total possible score. Score assigned based on payments per enrollee, by demographic group, physician fees and Medicaid fees compared to Medicare fees. States with higher reimbursement scored higher in this category.
DEMOGRAPHICS		
White (reference)	Reference	Equals 1 if respondent chose "white" as race; else equals

Variable Name	Expected Impact	Description
	group	0
African American	-	Equals 1 if respondent chose “black” as race; else equals 0
Asian	?	Equals 1 if respondent chose “Asian” as race; else equals 0
Native Hawaiian	?	Equals 1 if respondent chose “Native Hawaiian” as race; else equals 0
American Indian	?	Equals 1 if respondent chose “American Indian” as race; else equals 0
Other Race	?	Equals 1 if respondent chose “other race” as race; else equals 0
Multi Racial	?	Equals 1 if respondent chose “multi racial” as race; else equals 0
Hispanic	?	Equals 1 if respondent chose “Hispanic” as ethnicity; else equals 0
Age	+/-	Respondent’s stated age in years
Female	+	Equals 1 if respondent chose “female” as gender; else 0 equals male
FAMILY SITUATION		
Married	+	Equals 1 if respondent reports currently being married; else equals 0
Divorced	?	Equals 1 if respondent reports currently being divorced; else equals 0
Widowed	?	Equals 1 if respondent reports currently being widowed; else equals 0
Separated	?	Equals 1 if respondent reports currently being separated; else equals 0
Never Married (reference)	Reference group	Equals 1 if respondent reports never having married; else equals 0
Unmarried Couple	+	Equals 1 if respondent reports being a member of an unmarried couple; else equals 0
Having no Children	Reference group	The number of children less than 18 years of age residing in respondent’s household. Equals 1 if respondent reports no children; else equals 0
Having One Child	-	The number of children less than 18 years of age residing in respondent’s household. Equals 1 if respondent reports 1 children; else equals 0
Having Two Children	-	The number of children less than 18 years of age residing in respondent’s household. Equals 1 if respondent reports 2 children; else equals 0
Having Three Children	-	The number of children less than 18 years of age residing in respondent’s household. Equals 1 if respondent reports 3 children; else equals 0
Having Four Children	-	The number of children less than 18 years of age residing in respondent’s household. Equals 1 if respondent reports 4 children; else equals 0
Having Five or more Children	-	The number of children less than 18 years of age in respondent’s household. Equals 1 if respondent reports 5

Variable Name	Expected Impact	Description
		or more children; else equals 0
EDUCATION		
Never Attended School (reference)	Reference group	Respondent's reported highest education completed: equals 1 if never attended school or only kindergarten; else equals 0
Elementary	+	Respondent's reported highest education completed: equals 1 if respondent attended grades 1 through 8; else equals 0
Some High School	+	Respondent's reported highest education completed: equals 1 if respondent attended grades 9 through 11; else equals 0
High School Graduate	+	Equals 1 if respondent reported having completed high school or GED; else equals 0
Some College	+	Respondent's reported highest education completed: equals 1 if respondent attended college for 1 to 3 years; else equals 0
College Graduate	+	Equals 1 if respondent reported having completed 4 years of college or more; else equals 0
ECONOMICS		
Income <$10k	-	Equals 1 if respondent reported total family income less than $10,000; else equals 0
Income $10k to <$15k	-	Equals 1 if respondent reported total family income between $10,000 and less than $15,000; else equals 0
Income $15k to <$20k	-	Equals 1 if respondent reported total family income between $15,000 and less than $20,000; else equals 0
Income $20k to <$25k	-	Equals 1 if respondent reported total family income between $20,000 and less than $25,000; else equals 0
Income $25k to <$35k	-	Equals 1 if respondent reported total family income between $25,000 and less than $35,000; else equals 0
Income $35k to <$50k	-	Equals 1 if respondent reported total family income between $35,000 and less than $50,000; else equals 0
Income $50k to <$75k	-	Equals 1 if respondent reported total family income between $50,000 and less than $75,000; else equals 0
Income >$75k (reference)	Reference group	Equals 1 if respondent reported total family income greater than $75,000; else equals 0
Employed (reference)	Reference group	Employment status: equals 1 if respondent reported being employed for wages; else equals 0
Self-employed	+	Employment status: equals 1 if respondent reported being self-employed; else equals 0
Unemployed >1 Year	-	Employment status: equals 1 if respondent reported being unemployed for more than 1 year; else equals 0
Unemployed <1 Year	-	Employment status: equals 1 if respondent reported being unemployed for less than 1 year; else equals 0
Homemaker	?	Employment status: equals 1 if respondent reported being a homemaker; else equals 0
Student	?	Employment status: equals 1 if respondent reported being student; else equals 0
Retired	?	Employment status: equals 1 if respondent reported

Variable Name	Expected Impact	Description
		being retired; else equals 0
Unable to Work	-	Employment status: equals 1 if respondent reported being unable to work; else equals 0
Hours Worked Weekly	+/-	The combined number of hours respondent reported having worked weekly from all of their jobs and businesses
HEALTH		
Excellent Health	+	Equals 1 if respondent reported having excellent health in general; else equals 0
Very Good Health	+	Equals 1 if respondent reported having very good health in general; else equals 0
Good Health	+	Equals 1 if respondent reported having good health in general; else equals 0
Fair Health	+	Equals 1 if respondent reported having fair health in general; else equals 0
Poor Health (reference)	Reference group	Equals 1 if respondent reported having poor health in general; else equals 0
Days of Poor Physical Health in 1 Month	-	The number of days respondent reported having poor physical health in 1 month; else equals 0
Days of Poor Mental Health in 1 Month	-	The number of days respondent reported having poor mental health in 1 month; else equals 0
Days w/ Not Enough Sleep	-	The number of days respondent reported without enough sleep in 1 month; else equals 0

Source: Centers for Disease Control and Prevention: Behavioral Risk Factor Surveillance System (BRFSS) 2010 Data Files. Variables denoted with * came from Ramirez de Arellano & Wolfe, 2007.

Table 3.3 below provides descriptive statistics for each of the variables in the model, including the distribution and range of the data used in the regression analysis. It displays the sample size (excludes missing individual observations), the mean, standard deviation, and minimum/maximum value calculated for each variable. The descriptive statistical analysis reveals several notable characteristics in the dataset. The vast majority of participants in the sample are satisfied with their life (95%), indicating a skewed life satisfaction distribution. Such a skewed life satisfaction distribution may impact the regression analysis results and may require a representative random sampling to test whether the results from chosen regression analyses are adversely affected. Regardless, this disproportionate distribution is well documented in past well-being studies, as most people tend to rate themselves in the happy category, with only 5% of the population falling into the least three happy categories, on a 10-point scale (Frey & Stutzer, 2002a). The data shows only 16% of survey participants aged between 18 and 64 lacked health insurance coverage, compared to the national average of 18%. Since the number of participants who never attended school is extremely small (603), it was combined with individuals with elementary education as a reference group.

Table 3.3: Descriptive Statistics

Variable Name	**Sample Size, N=**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Life Satisfaction (dependent)	430,307	0.9460	0.2260	0	1
KEY EXPLANATORY VARIABLES					
No Health Insurance Coverage	449,858	0.1063	0.3082	0	1
Cannot Afford Doctor	449,950	0.1181	0.3227	0	1
Percent Medicaid Eligibility for State	449,927	0.5335	0.1555	0.2588	0.8480
Percent Medicaid Scope of Services for State	449,927	0.5933	0.1163	0.3340	0.8415
Percent Medicaid Quality of Care for State	449,927	0.3166	0.1719	-0.0220	0.7150
Percent Medicaid Reimbursement for State	439,160	0.4278	0.1502	0.0488	1
DEMOGRAPHICS					
White (reference)	444,704	0.7914	0.4063	0	1
African American	444,704	0.0814	0.2735	0	1
Asian	444,704	0.1742	0.1309	0	1
Native Hawaiian	444,704	0.0023	0.0476	0	1
American Indian	444,704	0.0136	0.1157	0	1
Other Race	444,704	0.0048	0.0693	0	1
Multi Racial	444,704	0.0173	0.1303	0	1
Hispanic	444,704	0.0717	0.2581	0	1
Age	446,855	56.791	16.489	18	99
Female	451,075	0.6229	0.4846	0	1
FAMILY SITUATION					
Married	448,928	0.5560	0.4968	0	1
Divorced	448,928	0.1402	0.3471	0	1
Widowed	448,928	0.1483	0.3554	0	1
Separated	448,928	0.0206	0.1421	0	1
Never Married (reference)	448,928	0.1142	0.3181	0	1
Unmarried Couple	448,928	0.0207	0.1423	0	1
Having no Children (reference)	449,356	0.7312	0.4433	0	1
Having One Child	449,356	0.1061	0.3080	0	1
Having Two Children	449,356	0.1005	0.3007	0	1
Having Three Children	449,356	0.0415	0.1995	0	1

Variable Name	**Sample Size, N=**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Having Four Children	449,356	0.0140	0.1175	0	1
Having Five or more Children	449,356	0.0065	0.0805	0	1
EDUCATION					
Never Attended School (reference)	449,465	0.0013	0.0366	0	1
Elementary	449,465	0.0327	0.1777	0	1
Some High School	449,465	0.6231	0.2417	0	1
High School Graduate	449,465	0.2992	0.4579	0	1
Some College	449,465	0.2656	0.4417	0	1
College Graduate	449,465	0.3388	0.4733	0	1
ECONOMICS					
Income <$10k	386,578	0.0578	0.2337	0	1
Income $10k to <$15k	386,578	0.0642	0.2451	0	1
Income $15k to <$20k	386,578	0.0818	0.2740	0	1
Income $20k to <$25k	386,578	0.1005	0.3006	0	1
Income $25k to <$35k	386,578	0.1211	0.3262	0	1
Income $35k to <$50k	386,578	0.1516	0.3586	0	1
Income $50k to <$75k	386,578	0.1565	0.3633	0	1
Income >$75k (reference)	386,578	0.2666	0.4422	0	1
Employed (reference)	448,822	0.3986	0.4896	0	1
Self-employed	448,822	0.0827	0.2754	0	1
Unemployed >1 Year	448,822	0.0326	0.1775	0	1
Unemployed <1 Year	448,822	0.0279	0.1646	0	1
Homemaker	448,822	0.0761	0.2651	0	1
Student	448,822	0.0159	0.1251	0	1
Retired	448,822	0.2949	0.4560	0	1
Unable to Work	448,822	0.0714	0.2575	0	1
Hours Worked Weekly	10,628	43.138	15.140	0	96
HEALTH					
Excellent Health	449,269	0.1745	0.3796	0	1
Very Good Health	449,269	0.3170	0.4653	0	1
Good Health	449,269	0.3071	0.4613	0	1
Fair Health	449,269	0.1395	0.3465	0	1
Poor Health (reference)	449,269	0.0618	0.2408	0	1
Days of Poor Physical Health in 1 Month	440,011	4.4560	8.9833	0	30
Days of Poor Mental Health in 1 Month	442,352	3.4410	7.8012	0	30
Days w/ Not Enough Sleep	441,990	7.6271	9.9768	0	30

Source: CDC, 2010; Ramirez de Arellano & Wolfe, 2007.

Appendix B provides a correlation matrix of the correlation coefficients for each pair of independent variables and their statistical significance. Some explanatory variables used in a regression analysis may be highly correlated with one another, meaning a change in one variable will result in a similar change in another. Statistically significant correlations suggest the correlation is not random. If a value has an asterisk at the end of it, it means the correlational value is statistically significant at a 90% confidence level or higher, signifying only a 10% probability that the statistical result is by random chance. Two asterisks represent a 95% confidence level or higher, and three asterisks mean a 99% confidence level or higher. The correlation coefficient indicates the magnitude (the closer to “1” or “-1” the greater the correlation) and direction of the correlation (negative values indicate the variables move in opposite directions and positive values indicate they move in the same direction). The correlation matrix of the independent variables is important because it may help detect instances of multicollinearity, which occurs when an explanatory variable is a close linear function of another variable. If multicollinearity occurs between two variables, and one of the variables is not statistically significant in the regression, it may be necessary to remove one of the variables to prevent upward bias in the standard error of the regression coefficient. This correlation matrix shows that the highest paired correlations are in the 0.70 range. As a general rule, correlational absolute values of 0.8 or greater may indicate multicollinearity. The paired correlations in this matrix do not seem to cause concern in the initial multicollinearity test, as they do not exceed the 0.80 correlation level.

In this chapter, I explained the conceptual framework for my regression equation, the source of my data, and the analytical methods I used to examine the impact of health insurance coverage, as well health care cost, and Medicaid factors on happiness and well-being. I described the theory and specification of my regression model to perform individual level statistical analysis that evaluate the impact of an array of variables on happiness, the most important of which are the health insurance coverage related variables. Although there is a large body of research on well-being, there are few, if any, existing studies that measure the direct effect of health insurance coverage on individual well-being. This study fills the gap by providing an answer to this particular question. In the next chapter, I review the result of this regression model and the significance, direction, and magnitude of regression coefficients for the regression model I selected for subsequent analysis.

Chapter Four

REGRESSION RESULTS

The previous chapter introduced the variables and broad causal model for the regression equation used to test the hypothesis of this study. This chapter presents the testing of the hypothesis that health insurance coverage, health care cost, and Medicaid factors impact well-being, and interprets the results. Moreover, I discuss the regression analyses and results of the two types of functional forms performed – Ordinary Least Squares (OLS) linear regression and binomial logistic regression. A summary of each functional form is provided, followed by a discussion of the potential errors and post-estimation tests to address potential multicollinearity and heteroskedasticity issues for each model. The remaining discussion will be focused on the preferred regression model.

A regression coefficient represents the estimated unit change in the dependent variable relative to a one unit change in an explanatory variable, holding all other explanatory variables in the equation constant (Studenmund, 2011). If a coefficient is positive, it indicates a positive relationship between the explanatory variable and the dependent variable. In contrast, if a coefficient is negative, it indicates a negative relationship between the explanatory variable and the dependent variable. A standard error is the square root of the variance in a given coefficient and represents the accuracy of the coefficient estimate (Studenmund, 2011). For example, a standard error that is large relative to corresponding regression coefficients indicates that the coefficient does not accurately capture the effect of the explanatory variable on the dependent variable. Since standard errors typically shrink in size as the sample size grows, larger sample sizes tend to have more accurate regression coefficients.

Data within a sample fall along various points within an X-Y axis. Therefore, choosing a functional form that will best fit or intersect these points is important to ensure that the estimated regression coefficients are not biased. Since my dependent variable in the regression equation is coded as dichotomous, this restricts the types of regression forms available to test the hypothesis. Methods such as log/linear and log/log are not appropriate as this would require taking the log of the variables, something that can be done if zero is a potential answer. With the majority of the variables in this equation being dichotomous, taking the log of any of these variables would be illogical. Thus, there are two regression models that best measure the shapes that exemplify the expected underlying economic principals, the OLS linear and logistic regression models (Studenmund, 2011).

Multicollinearity

Multicollinearity exists when the linear relationship between two independent variables is strong enough that the estimated coefficients in the regression are significantly affected. Thus, when one variable moves in one direction, a correlated variable moves equally either in the same or opposite direction. Multicollinearity results in greater variance in the estimates of regression coefficients that can lead to rejecting the impact of an independent variable that is actually significant. I evaluated each regression equation for potential multicollinearity. My prior simple correlation result of paired independent variables indicated that there is no multicollinearity in the initial test. To further test for multicollinearity, I performed the Variance Inflation Factor (VIF) test to detect for multicollinearity that may not have been identified in the initial simple correlation test. As a general rule, any variable that has a VIF greater than five and whose regression results were not significant, likely have multicollinearity issues.

The VIF test performed after running the linear regression indicates potential collinearity issues because relatively high VIF are present in six of the variables (College Graduate, Some

College, High School Graduate, Very Good Health, Good Health, Excellent Health), with VIF scores of 5 or greater (see Table 4.1 below). Even though all of these variables have significant regression results, as a precaution, the high VIF scores suggest that adjustment to the model or correction for multicollinearity may be necessary.

Corrections for multicollinearity include increasing the sample size and dropping some of the variables. As the BRFSS data set is already an extremely large data set of over 450,000 observations, expanding the size of the data set is not possible and is outside the scope of this study. Trying to correct for multicollinearity by dropping explanatory variables might be worse than not correcting for multicollinearity since dropping explanatory variables can introduce another form of bias known as omitted variable bias (Studenmund, 2011). Omitted variable bias occurs when a regression model fails to account for all of the major causal factors, causing bias in the regression results. To test the effect that the potentially collinear variables were having on the regression equations, I dropped each variable in turn to determine whether the variable had a negative effect on the outcome or not. In some instances when collinear variables were dropped, other variables took on significance, however the variables that were collinear were not affected. Furthermore, these six variables are not redundant, thus dropping them could create omitted variable bias. Ultimately, I chose to keep all six variables despite some potential multicollinearity.

Heteroskedasticity

Heteroskedasticity occurs when there is a potential for the error term to vary depending on the observations drawn from the data set, which frequently exists with data sets comprised of widely ranging observed values of the dependent variable. If the variance of the error term changes, the standard error for the estimated coefficients can change depending on the observations. This can lead to errors in interpreting which variables are significant. Among the consequences of not correcting for heteroskedasticity is the potential for unreliable hypothesis testing due to biased standard error statistics. To evaluate heteroskedasticity among the continuous variables in my linear regression model, I performed the Breusch-Pagan/Cook-Weisberg test. This test examines all the explanatory variables at once and shows whether the estimated variances of the standard errors are dependent on the independent variables. The resulting p-value of the test was 0.0000, indicating that there is a 99.99% chance that my model has heteroskedasticity issues. Next, I ran Szroeter's test for homoscedasticity, which assesses each explanatory variable individually and assigns a probability value to each variable to identify specific variables that may be causing heteroskedasticity. A probability of less than 0.10 indicates heteroskedasticity. The result of the Szroeter's test indicates that all but one explanatory variable, having five or more children, suffer from heteroskedasticity. Therefore, I reanalyzed the regression with correction for heteroskedasticity. Results of the corrected regression equations using heteroskedasticity-corrected standard errors are presented alongside the uncorrected equation for the OLS linear regression. Since heteroskedasticity biases the standard errors of regression coefficients, correcting for this bias could account for heterogeneity and lack of normality while improving statistical significance and without altering the values of the coefficients. However, there are some instances where correcting for heteroskedasticity could result in a loss of statistical significance.

Ordinary Least Squares Linear Regression

The OLS is the best known of all regression techniques, which accounts for random errors in a data set by calculating the estimated slope coefficients to minimize the difference between the actual quantitative effect on each observation and the estimated effect produced from the aggregate data (Studenmund, 2011). Minimizing this difference (the residual) allows the researcher to consider whether the equation is predictive of similar outcomes among larger populations. The simplest functional form is a linear regression, which works for models that meet the following two assumptions: (1) there is a linear relationship between the dependent and independent variables; and (2) this relationship is additive (i.e. Y= x1 + x3 +…+xN). Linear regression estimates how much the dependent variable changes when the independent variable changes one unit, thus isolating the effect of life satisfaction while holding all other variables constant. The right side of the equation (the independent variable) refers to linear probability while the left side measures the probability that the dependent variable is dichotomous and equal to one (Studenmund, 2011). The problem with using OLS when the dependent variable is dichotomous is the estimated line has an "unboundedness" problem because it could predict a value greater than one and less than zero. This does not make sense since the observed dependent variable does not exceed one or extend below zero. This can be temporarily solved by ignoring values that exceed the known limits so that anything greater than one would be treated as equaling one, and anything less than zero would equal zero. However, the influence of all the independent variables may not be captured completely and accurately.

Table 4.1 below lists the uncorrected and corrected regression results of the OLS linear model for the variables in the regression model, the estimated coefficients and the standard error (in parentheses). Asterisks indicate statistical significant variables. While running the regression model, the variable Hours Worked was automatically dropped due to multicollinearity issue. Since there are only a small number of participants who never attended school, these participants are combined with the elementary school category to create a reference group. As a result, the revised regression resulted in statistical significance in all the education variables compared to the original model (not shown) that only excluded the category Never Attended School.

The model corrected for heteroskedasticity yielded one less statistical significant variable than the uncorrected model, resulting in a loss of significance in variable Other Race. The overall fit of the model was very good, given the adjusted R^2 of 0.1893. This can be roughly interpreted as approximately 18.93% of the variance in life satisfaction is accounted for by the linear regression model. Since this model does not explicitly include personality traits and characteristics that could explain approximately 50% of the variability in happiness, the overall model fit suggests that most of the significant variables are accounted for in my model.

Table 4.1: OLS Linear Regression Model

Variable Name	**OLS Estimated Coefficients and (Standard Errors)**	**Variance Inflation Factor (VIF)**	**OLS Estimated Coefficients and (Standard Errors)** ***Corrected for Heteroskedasticity***
KEY EXPLANATORY VARIABLES			
No Health Insurance Coverage	-0.0093*** (0.0013)	1.33	-0.0093*** (0.0017)
Cannot Afford Doctor	-0.0429*** (0.0012)	1.29	-0.0429*** (0.0018)
Percent Medicaid Eligibility for State	-0.0047 (0.0029)	1.77	-0.0047 (0.0029)
Percent Medicaid Scope of Services for State	-0.0206*** (0.0040)	1.81	-0.0206*** (0.0040)
Percent Medicaid Quality of Care for State	-0.0021 (0.0020)	1.06	-0.0021 (0.0021)
Percent Medicaid Reimbursement for State	0.0007 (0.0023)	1.05	0.0007 (0.0023)
DEMOGRAPHICS			
African American	0.0141*** (0.0013)	1.11	0.0141*** (0.0015)
Asian	0.0048* (0.0026)	1.02	0.0048** (0.0020)
Native Hawaiian	0.0005 (0.0086)	1.00	0.0005 (0.0102)
American Indian	0.0200*** (0.0030)	1.02	0.0200*** (0.0036)
Other Race	-0.0092* (0.0053)	1.00	-0.0092 (0.0064)
Multi Racial	0.0030 (0.0026)	1.01	0.0030 (0.0032)
Hispanic	0.0194*** (0.0015)	1.15	0.0194*** (0.0016)
Age	0.00005 (0.00003)	2.98	0.00005 (0.00003)
Female	0.0130*** (0.0007)	1.12	0.0130*** (0.0007)
FAMILY SITUATION			

Variable Name	**OLS Estimated Coefficients and (Standard Errors)**	**Variance Inflation Factor (VIF)**	**OLS Estimated Coefficients and (Standard Errors)** ***Corrected for Heteroskedasticity***
Married	0.0308*** (0.0012)	3.39	0.0308*** (0.0015)
Divorced	0.0009 (0.0014)	2.20	0.0009 (0.0018)
Widowed	0.0191*** (0.0016)	2.62	0.0191*** (0.0019)
Separated	-0.0163*** (0.0026)	1.20	-0.0163*** (0.0041)
Unmarried Couple	0.0240*** (0.0025)	1.19	0.0240*** (0.0029)
Having One Child	0.0046*** (0.0012)	1.24	0.0046*** (0.0013)
Having Two Children	0.0091*** (0.0013)	1.37	0.0091*** (0.0012)
Having Three Children	0.0123*** (0.0018)	1.21	0.0123*** (0.0017)
Having Four Children	0.0098*** (0.0029)	1.08	0.0098*** (0.0029)
Having Five or more Children	0.0140*** (0.0042)	1.04	0.0140*** (0.0043)
EDUCATION			
Some High School	-0.0130*** (0.0027)	3.10	-0.0130*** (0.0034)
High School Graduate	-0.0238*** (0.0023)	9.77	-0.0238*** (0.0029)
Some College	-0.0316*** (0.0024)	9.79	-0.0316*** (0.0030)
College Graduate	-0.0341*** (0.0024)	11.74	-0.0341*** (0.0030)
ECONOMICS			
Income <$10k	-0.0422*** (0.0020)	1.65	-0.0422*** (0.0029)
Income $10k to <$15k	-0.0247*** (0.0018)	1.62	-0.0247*** (0.0024)
Income $15k to <$20k	-0.0158*** (0.0016)	1.65	-0.0158*** (0.0019)
Income $20k to <$25k	-0.0112*** (0.0014)	1.62	-0.0112*** (0.0015)
Income $25k to <$35k	-0.0049*** (0.0013)	1.58	-0049*** (0.0012)
Income $35k to <$50k	-0.0030*** (0.0011)	1.51	-0030*** (0.0009)
Income $50k to <$75k	-0.0001 (0.0011)	1.39	0.00001 (0.0008)

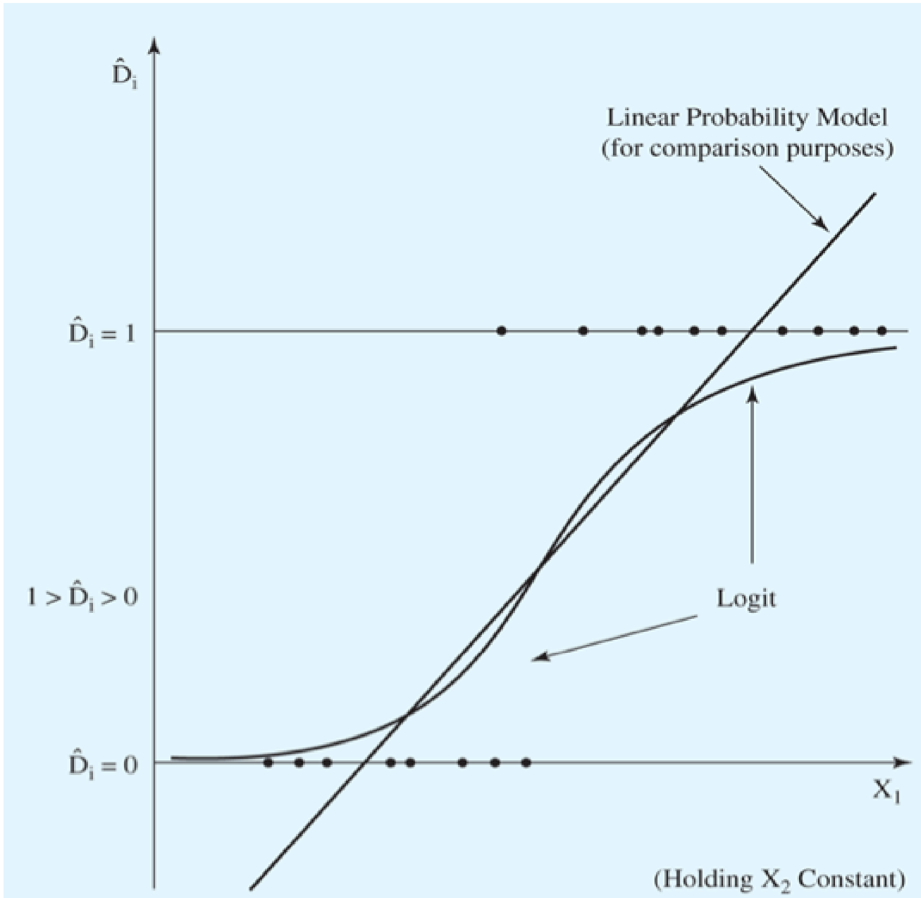
Variable Name	**OLS Estimated Coefficients and (Standard Errors)**	**Variance Inflation Factor (VIF)**	**OLS Estimated Coefficients and (Standard Errors) *Corrected for Heteroskedasticity***
Self-employed	-0.0004 (0.0013)	1.14	-0.0004 (0.0011)
Unemployed >1 Year	-0.0659*** (0.0021)	1.13	-0.0659*** (0.0034)
Unemployed <1 Year	-0.0459*** (0.0021)	1.09	-0.0459*** (0.0031)
Homemaker	-0.0004 (0.0015)	1.21	-0.0004 (0.0012)
Student	0.0155** (0.0030)	1.09	0.0155*** (0.0032)
Retired	0.0026** (0.0011)	2.11	0.0026** (0.0009)
Unable to Work	-0.0536*** (0.0017)	1.56	-0.0536*** (0.0028)
HEALTH			
Excellent Health	0.0995*** (0.0021)	5.81	0.0995*** (0.0033)
Very Good Health	0.0992*** (0.0020)	7.77	0.0992*** (0.0033)
Good Health	0.0949*** (0.0019)	6.83	0.0949*** (0.0033)
Fair Health	0.0714*** (0.0019)	3.36	0.0714*** (0.0034)
Days of Poor Physical Health in 1 Month	-0.0003*** (0.00005)	1.79	-0.0003*** (0.00007)
Days of Poor Mental Health in 1 Month	-0.0079*** (0.00005)	1.31	-0.0079*** (0.00009)
Days w/ Not Enough Sleep	-0.0011*** (0.00003)	1.24	-0.0011*** (0.00004)
Constant	0.9216	N/A	0.9216
R^2	0.1894	N/A	0.1894
Adjusted R^2	0.1893	N/A	N/A
Number of Observations	340,580	N/A	340,580
Number of Significant Variables	40	N/A	39
Breusch-Pagan/Cook-Weisberg test for heteroskedasticity			
Chi2(9) = 309,844.92			
Prob > Chi2 = 0.0000			
*Significant at the 90% confidence level (based on a two-tail test) **Significant at the 95% confidence level (based on a two-tail test) ****Significant at the 99% or greater confidence level (based on a two-tail test)			

Binomial Logistic Regression

Of the two regression models, the binomial logistic regression is the most appropriate for equations that have dichotomous dependent variables. This is the case in my study since it measures the causal factors that impact whether individuals are satisfied with their life. The outcome might be dichotomous by nature (a person either has health insurance coverage or not) or represent a dichotomization of a continuous or categorical variable (where very satisfied and satisfied with life are coded as 1 and very dissatisfied and dissatisfied with life are coded as 0). Outcome variables in logistic regression are conventionally coded as 0-1, with 0 representing the absence of a characteristic and 1 representing its presence.

Compared to a linear probability model that offers a straight line to predict the value of variables, binomial logistic regression fits an "S-shape" curve rather than a straight line, which ensures predicted values are bounded by zero and one (see Figure 4.1 below). The binomial logistic regression model is quite valuable to most researchers since real-world data are often described well by S-shape patterns similar to the figure below. This model avoids the major problem in linear probability model when encountering dichotomous dependent variables because it avoids the "unboundedness" problem present in the linear probability estimation technique using OLS. In other words, although the dependent variable only takes on a value of zero or one, in a linear model the expected value of the dependent variable is not limited by zero or one (Studenmund, 2011). Thus, OLS results are essentially meaningless for dichotomous dependent variables.

Figure 4.1: Comparing Linear and Logistic Regression Models



Source: Studenmund, 2011

Logistic regression is estimated using maximum likelihood, an iterative estimation technique that maximizes the likelihood of the sample data set being observed and is useful for equations with nonlinear coefficients (Studenmund, 2011). Specifically, the values of the estimated parameters are adjusted iteratively until the maximum likelihood value for the estimated parameters is obtained. Logistic regression applies maximum likelihood estimation after transforming the dependent variables into logit variables, which estimates the odds of the dependent variable to be 1 (y=1), which is the probability that some event happens. Unlike OLS regression, logistic regression does not assume a linear relationship between the raw values of the independent variables and the raw values of the dependent, does not require normally distributed variables, does not assume homoscedasticity, and in general has less stringent requirements.

Table 4.2 below shows the binomial logistic regression results for the theoretical model described in the previous chapter. The results include the following: (1) Odds Ratio [exp($\boldsymbol{\beta}$)] and the corresponding standard error for each predictor variable; (2) the percentage change in odds for both uncorrected and corrected equations. I identify statistically significant results at the 90%, 95%, and 99% confidence level with corresponding asterisks, as well as a report of total observations (N) and pseudo R^2.

The logistic regression method calculates a "pseudo-R^2" to measure overall fit of the regression model, which is the average of the percentage of ones (satisfied or very satisfied with life) explained correctly and the percentage of zeros (dissatisfied or very dissatisfied with life) explained correctly (Studenmund, 2011). Logistic regression converts the estimated coefficients into an odds ratio [exp($\boldsymbol{\beta}$)] which can be translated into a more easily understood term, percentage change in odds, by using the equation [exp($\boldsymbol{\beta}$) – 1]*100. As a result, odds ratios less than one indicate a negative effect, while odds ratios greater than one denote a positive effect.

Although STATA does not have a built-in multicollinearity test for logistic regression models, I downloaded the collin.ado user-written program to perform a multicollinearity test on my logistic regression model. The result confirmed high VIF scores for the same six variables found in the VIF test performed on the linear regression model. Unlike linear regression that uses the least squares estimation, logistic regression analysis uses maximum likelihood estimation, and therefore heteroskedasticity is not a concern. All of the six variables with high VIF scores have significant regression results, which means that adjustment to the model or correction for multicollinearity is not necessary.

As discussed earlier, the vast majority of the participants in my sample are satisfied with their life (95%), indicating a skewed life satisfaction distribution. This skewed life satisfaction distribution may require a more representative random sampling to test whether the results from chosen regression analyses are adversely affected. According to Studenmund (2011), it is important to make sure that a logit sample contains a reasonable representation of both alternative choices, especially for smaller samples. To test this effect, I created five random samples with equal representation of life satisfaction from the larger data set. The logistic regression analysis of these samples demonstrate striking consistency with results from the larger data set, with most showing larger happiness effects among the key explanatory variables and better model fit. However, the following variables were excluded from these models given their small sample size and lower likelihood of being randomly selected into the smaller data set: Asian, Native Hawaiian, American Indian, Other Race, Multi Racial, Some High School, Unemployed > 1 Year, and Unemployed < 1 year. Since the exclusion of these variables would most likely lead to omitted variable bias and since this study uses a rather large data sample, I decided to continue with the regression analysis of the larger data set.

Table 4.2: Preferred Regression Model - Binomial Logistic Regression

Variable Name	**Odds Ratio exp(β)**	**% Change in Odds of being Happy for Unit Increase in Independent Variable**	**VIF**
KEY EXPLANATORY VARIABLES			
No Health Insurance Coverage	0.9061*** (0.0237)	-9.4%	1.33
Cannot Afford Doctor	0.5928*** (0.0131)	-40.7%	1.29
Percent Medicaid Eligibility in State	0.8526** (0.0637)	-14.7%	1.78
Percent Medicaid Scope of Services in State	0.5838*** (0.0587)	-41.6%	1.81

Variable Name	**Odds Ratio exp(β)**	**% Change in Odds of being Happy for Unit Increase in Independent Variable**	**VIF**
Percent Medicaid Quality of Care in State	0.9755 (0.0505)	-2.4%	1.07
Percent Medicaid Reimbursement in State	1.0638 (0.0647)	6.4%	1.05
DEMOGRAPHICS			
African American	1.2367*** (0.0379)	23.7%	1.12
Asian	1.2302** (0.1060)	23.0%	1.02
Native Hawaiian	0.9575 (0.1843)	-4.2%	1.00
American Indian	1.4298*** (0.0938)	43.0%	1.02
Other Race	0.8395 (0.0944)	-16.0%	1.00
Multi Racial	1.1013* (0.0603)	10.1%	1.01
Hispanic	1.4404*** (0.0541)	44.0%	1.16
Age	1.0024** (0.0009)	0.2%	2.97
Female	1.2673*** (0.0240)	26.7%	1.12
FAMILY SITUATION			
Married	2.1803*** (0.0626)	118%	3.38
Divorced	1.0895*** (0.0314)	9.0%	2.19
Widowed	1.3670*** (0.0508)	36.7%	2.61
Separated	0.9238* (0.0421)	-7.6%	1.20
Unmarried Couple	1.5055*** (0.0847)	50.6%	1.19
Having One Child	1.0615** (0.0312)	6.2%	1.24
Having Two Children	1.1903*** (0.0410)	19.0%	1.37
Having Three Children	1.3133*** (0.0657)	31.3%	1.20
Having Four Children	1.1466*** (0.0871)	14.7%	1.08

Variable Name	**Odds Ratio exp(β)**	**% Change in Odds of being Happy for Unit Increase in Independent Variable**	**VIF**
Having Five or more Children	1.2699** (0.1394)	27.0%	1.04
EDUCATION			
Some High School	0.8533*** (0.0475)	-14.7%	3.06
High School Graduate	0.7777*** (0.0393)	-22.2%	9.51
Some College	0.6565*** (0.0337)	-34.3%	9.49
College Graduate	0.6145*** (0.0326)	-38.5%	11.38
ECONOMICS			
Income <$10k	0.4735*** (0.0207)	-52.6%	1.66
Income $10k to <$15k	0.5048*** (0.0216)	-49.5%	1.63
Income $15k to <$20k	0.5339*** (0.0220)	-46.6%	1.66
Income $20k to <$25k	0.5525*** (0.0219)	-44.7%	1.62
Income $25k to <$35k	0.6203*** (0.0240)	-38.0%	1.59
Income $35k to <$50k	0.6638*** (0.0246)	-33.6%	1.51
Income $50k to <$75k	0.7978*** (0.0304)	-20.2%	1.39
Self-employed	0.9525 (0.0364)	-4.7%	1.14
Unemployed >1 Year	0.4580*** (0.0166)	-54.2%	1.13
Unemployed <1 Year	0.4868*** (0.0193)	-51.3%	1.09
Homemaker	1.0365 (0.0467)	3.7%	1.21
Student	1.1239 (0.0802)	12.4%	1.08
Retired	1.2009*** (0.0383)	20.1%	2.11
Unable to Work	0.6951*** (0.0212)	-30.5%	1.56
HEALTH			
Excellent Health	4.5638*** (0.2167)	356.4%	5.75
Very Good Health	3.2881***	228.8%	7.66

Variable Name	Odds Ratio exp(β)	% Change in Odds of being Happy for Unit Increase in Independent Variable	VIF
	(0.1232)		
Good Health	2.3338*** (0.0764)	133.4%	6.76
Fair Health	1.5134*** (0.0429)	51.3%	3.34
Days of Poor Physical Health in 1 Month	0.9963*** (0.0010)	-0.4%	1.80
Days of Poor Mental Health in 1 Month	0.9284*** (0.0007)	-7.2%	1.32
Days w/ Not Enough Sleep	0.9759*** (0.0007)	-2.4%	1.24
Constant	34.115		N/A
Pseudo R^2	0.2893		N/A
Prob > Chi2	0.0000		N/A
LR Chi2	41,001.03		N/A
Number of Observations	340,580		N/A
Number of Significant Variables	43		N/A
*Significant at the 90% confidence level (based on a two-tail test) **Significant at the 95% confidence level (based on a two-tail test) ****Significant at the 99% or greater confidence level (based on a two-tail test)			

Overall Model Fit

The model's overall goodness of fit, as measured by pseudo R^2, is 0.2893. This means the independent variables accounts for 28.93% of the variance in life satisfaction. The model chi-square tests whether all the coefficients in the model are different from zero. Thus the chi-square of 0.0000 signifies that the overall model is 99.99% statistically significant and that the model fits the data very well. The classification table (Table 4.3) below shows the percentage of correct predictions for each of the levels of the dependent variable in the logistic regression model. It assumes that if the predicted value is greater than or equal to 0.5 and the actual value was 1, it was considered a correct prediction, or a "hit." A predicted value that was lower than 0.5 and the actual value was zero also qualified as a "hit." Any other outcome is categorized as a "miss." The hit ratio is calculated by dividing the number of hits by the total number of fitted observations and as a result, the life satisfaction model has an overall hit ratio of 94.86%. This indicates that overall, the model equation correctly predicts occurrence of life satisfaction approximately 94.86% of the time. Another way to assess the fit of the model is to use the *estat gof* command in STATA to find the Pearson goodness-of-fit chi-squared value. This test indicates that the model fits reasonably well because the goodness-of-fit chi-squared test is not statistically significant (Prob > chi^2 = 1.000). If the test had been statistically significant, it would indicate that the data do not fit the model well.

Table 4.3: Classification Table

		PREDICTED		
		Life Satisfaction		
OBSERVED		Is Not Satisfied with Life	Is Satisfied with Life	Percentage Correct Prediction
Life Satisfaction	Is Not Satisfied with Life	319,564	14,612	95.63%
	Is Satisfied with Life	2,870	3,534	44.82%
Overall Success Rate				**94.87%**

*Calculated based on 50% as a cut-off for positive predictions.

Expectations and Results

A comparison of the expected and actual signs shows that with the exception of a few variables, the model's significant variables returned the expected signs. However, several predictors, including African Americans, number of children, Percent of Medicaid Eligibility, Percent of Medicaid Scope, and all four education variables produced the opposite sign I expected. Firstly, although most existing happiness studies indicates African Americans are generally less happy than their white counterparts, my regression result reveals that African Americans have 23.7% higher odds of being satisfied with life compared to their white counterparts.

Secondly, my regression result indicates that each additional child added to the household increases the odds of life satisfaction, with the first child increasing the odds ratio by 6.2%, the second child by 19%, the third child by 31.3%, the fourth by 14.7%, and five or more children by 27%. Studies have shown that the stress of parenting may be responsible for the slight decline in parents' happiness and well-being. However, my study shows the opposite effect. Unlike other data samples, the BRFSS survey measures the number of children residing in the respondent's household rather than number of children of the respondent. Thus, the number of children captured in this data sample does not necessarily reflect the respondents being actual parents of the children reported.

The third predictor indicates that individuals residing in states with higher percentage of Medicaid Eligibility and Medicaid Scope of Services have lower odds of being happy, rather than being happier. Initially, the result was somewhat puzzling since it has the opposite sign from expectation. However, in thinking more in-depth about this issue, I came up with the following explanations for this negative outcome: (1) individuals residing in states with more generous Medicaid eligibility and scope of services may have higher tax obligations to pay for these programs; (2) Medicaid variables capture other state effects not attributed solely to Medicaid programs (i.e. economic growth, job opportunities); (3) Medicaid scorings can be somewhat subjective; (4) perception of Medicaid generosity may vary from actual generosity; and (5) most people may not be knowledgeable about the Medicaid programs in their states and how those benefits compare to other states.

Education was the last broad factor that produced unexpected signs even though several studies show that higher education typically increases individuals' happiness. Originally, I held the group Never Attended School as a reference group. However, since this group only has 603 observations compared to the total 449,465 observations in the education category, using this group as a reference resulted in insignificant outcomes for all education variables. When combined with Elementary education group as a reference group, the regression result produced significant but negative outcomes for all the education variables. Some possible explanations for the negative odds ratio for each level of education are as follows: higher education could correspond with other factors not captured in my regression model that could lower the happiness level, such as more stressful occupations, increased level of responsibility, longer work hours, less time for leisure activities, etc. Furthermore, this study uses the data set from 2010, representing the peak of the Great Recession that could potentially capture some effects unique to this time period. Greater economic instability could translate to increased financial uncertainties and insecurities, regardless of education levels. Otherwise, this study is, perhaps, providing proof that ignorance really is bliss. Table 4.4 below illustrates the expected and actual signs for each of the variables.

Table 4.4: Expected and Actual Signs of Explanatory Variables

Variable	Exp	Act	Variable	Exp	Act
KEY EXPLANATORY VARIABLES			**EDUCATION**		
No Health Insurance Coverage	-	-	Some High School	+	-
Cannot Afford Doctor	-	-	High School	+	-
Pct Medicaid Eligibility in State	+	-	Some College	+	-
Pct Medicaid Scope of Services in State	+	-	College Graduate	+	-
Pct Medicaid Quality of Care in State	+	NS	**ECONOMICS**		
Pct Medicaid Reimbursement in State	+	NS	Income <$10k	-	-
DEMOGRAPHICS			Income $10k to <15k	-	-
African American	-	+	Income $15k to <$20k	-	-
Asian	?	+	Income $20k to <$25k	-	-
Native Hawaiian	?	NS	Income $25k to <$35k	-	-
American Indian	?	+	Income $35k to <$50k	-	-
Other Race	?	NS	Income $50k to <$75k	-	-
Multi Racial	?	+	Self-employed	+	NS
Hispanic	?	+	Unemployed >1 Year	-	-
Age	+/-	+	Unemployed < 1Year	-	-
Female	+	+	Homemaker	?	NS
FAMILY SITUATION			Student	?	NS
Married	+	+	Retired	?	+
Divorced	?	+	Unable to Work	-	-
Widowed	?	+	**HEALTH**		
Separated	?	+	Excellent Health	+	+
Unmarried Couple	?	+	Very Good Health	+	+
One Child	-	+	Good Health	+	+
Two Children	-	+	Fair Health	+	+
Three Children	-	+	Days of Poor Physical Health in 1 Month	-	-
Four Children	-	+	Days of Poor Mental health in 1 Month	-	-
Five or More Children	-	+	Days of not Enough Sleep in 1 Month	-	-

*NS denotes non-significant variables.

Interaction Variables

This section examines the effect of an interaction term on the results of the equation. An interaction term is a variable that results from the multiplication of two variables, which captures the effect of both of these variables increasing together. Thus, one can test the combined influence of explanatory variables rather than just the influence of one, holding all other variables constant, as is typically done in regression analysis. Interactions with significant results contain "interaction effects" as a way to account for predictors that interact. I created a series of interaction variables that combined the interactions of my key independent variables: Medicaid rankings, lack of health insurance coverage, and not being able to see a doctor due to cost with various income groups, race, age, health characteristics, employment and health status. The following table (Table 4.5) shows the logistic regression model with significant interactions. The interaction variables were initially added to my model one at a time, culminating with the final regression model that included the significant interactions.

The results show that individuals who are self-employed residing in states with higher Medicaid quality of care ranking have 56% higher odds of being satisfied with life. Individuals who have been unemployed for more than one year that reside in states with higher Medicaid quality of care ranking have 51% higher odds of being happy. Individuals with household income between $10,000 and $15,000 residing in states with higher Medicaid quality of care ranking have 45% greater odds of being happy. Furthermore, individuals with household income between $20,000 and $25,000 residing in states with higher Medicaid reimbursement ranking are 39% more likely to be satisfied with life. The interactions between not being able to pay for a doctor due to cost and various income levels show that individuals with household income between $25,000 and $75,000 have 13% to 23% greater odds of not being satisfied with life. This suggests the inability to pay for a doctor significantly decreases the likelihood of being happy regardless of income level. Even more surprisingly, those with excellent and very good health who either cannot afford a doctor or do not have health insurance coverage are 16% to 35% less likely to be happy. This happens despite the fact that excellent and very good health by themselves are among the strongest predictors of life satisfaction as they increase the odds of having life satisfaction by 356% and 228%, respectively. This suggests that even for individuals with excellent and very good health, the negative effect of not having health insurance or not being able to see a doctor due to cost is extremely substantial.

Table 4.5: Logistic Regression with Significant Interactions

Variable Name	**Odds Ratio EXP(β)**	**% Change in Odds of being Happy for Unit Increase in Independent Variable**
KEY EXPLANATORY VARIABLES		
No Health Insurance Coverage	0.9514* (0.0281)	-4.9%
Cannot Afford Doctor	0.6757*** (0.0186)	-32.4%
Percent Medicaid Eligibility in State	0.8541** (0.0638)	-14.6%
Percent Medicaid Scope of Services in State	0.5839*** (0.0587)	-41.6%
Percent Medicaid Quality of Care in State	0.8713** (0.0513)	-12.9%
Percent Medicaid Reimbursement in State	1.0187 (0.0664)	1.9%
DEMOGRAPHICS		
African American	1.2375*** (0.0379)	23.8%
Asian	1.2339** (0.1064)	23.4%
Native Hawaiian	0.9638 (0.1857)	-3.6%
American Indian	1.4294*** (0.0934)	42.9%
Other Race	0.8424 (0.0944)	-15.8%
Multi Racial	1.1050* (0.0603)	10.5%

Variable Name	Odds Ratio EXP(β)	% Change in Odds of being Happy for Unit Increase in Independent Variable
Hispanic	1.4335*** (0.0538)	43.6%
Age	1.0023*** (0.0009)	0.2%
Female	1.2682*** (0.0241)	26.8%
FAMILY SITUATION		
Married	2.1676*** (0.0622)	116.8%
Divorced	1.0886*** (0.0313)	8.9%
Widowed	1.3675*** (0.0508)	36.8%
Separated	0.9208* (0.0419)	-7.9%
Unmarried Couple	1.5132*** (0.0850)	51.3%
Having One Child	1.0645** (0.0312)	6.4%
Having Two Children	1.1944*** (0.0411)	19.4%
Having Three Children	1.3194*** (0.0659)	31.9%
Having Four Children	1.1528* (0.0874)	15.3%
Having Five or more Children	1.2791** (0.1399)	27.9%
EDUCATION		
Some High School	0.8561*** (0.0475)	-14.4%
High School Graduate	0.7826*** (0.0394)	-21.7%
Some College	0.6607*** (0.0338)	-33.9%
College Graduate	0.6146*** (0.0325)	-38.5%
ECONOMICS		
Income <$10k	0.4747*** (0.0219)	-52.5%
Income $10k to <$15k	0.4496*** (0.0291)	-55.0%
Income $15k to <$20k	0.5364*** (0.0222)	-46.4%
Income $20k to <$25k	0.4838***	-51.6%

Variable Name	Odds Ratio EXP(β)	% Change in Odds of being Happy for Unit Increase in Independent Variable
	(0.0401)	
Income $25k to <$35k	0.6565*** (0.0275)	-34.3%
Income $35k to <$50k	0.7161*** (0.0283)	-28.4%
Income $50k to <$75k	0.8330*** (0.0335)	-16.7%
Self-employed	0.8422** (0.0640)	-15.8%
Unemployed >1 Year	0.4032*** (0.0277)	-59.7%
Unemployed <1 Year	0.4935*** (0.0195)	-50.6%
Homemaker	1.0442 (0.0470)	4.4%
Student	1.1311* (0.0806)	13.1%
Retired	1.2145*** (0.0389)	21.5%
Unable to Work	0.7045*** (0.0214)	-29.7%
HEALTH		
Excellent Health	5.4664*** (0.2934)	446.6%
Very Good Health	3.7330*** (0.1519)	273.3%
Good Health	2.3571*** (0.0770)	135.7%
Fair Health	1.5149*** (0.0428)	51.5%
Days of Poor Physical Health in 1 Month	0.9964*** (0.0009)	-0.4%
Days of Poor Mental Health in 1 Month	0.9285*** (0.0007)	-7.1%
Days w/ Not Enough Sleep	0.9759*** (0.0007)	-2.4%
INTERACTION VARIABLES		
Medicaid Quality of Care * Self-employed	1.5569** (0.3313)	55.7%
Medicaid Quality of Care * Unemployed > 1 Year	1.5103** (0.2749)	51.0%
Medicaid Quality of Care * Income $10k to <$15k	1.4514** (0.2185)	45.1%
Medicaid Reimbursement * Income $20k to	1.3918*	39.2%

Variable Name	Odds Ratio EXP(β)	% Change in Odds of being Happy for Unit Increase in Independent Variable
<$25k	(0.2401)	
Cannot Afford Doctor * Income $25k to <$35k	0.8664** (0.0506)	-13.4%
Cannot Afford Doctor * Income $35k to <$50k	0.7693*** (0.0473)	-23.1%
Cannot Afford Doctor * Income $50k to <$75k	0.8294** (0.0629)	-17.1%
Cannot Afford Doctor * Excellent Health	0.6478*** (0.0609)	-35.2%
Cannot Afford Doctor * Very Good Health	0.7131*** (0.0413)	-28.7%
No Health Insurance Coverage * Excellent Health	0.6930*** (0.0659)	-30.7%
No Health Insurance Coverage * Very Good Health	0.8384*** (0.0529)	-16.2%
Constant	34.876	
Pseudo R^2	0.2905	
Prob > chi2	0.0000	
LR chi2	41,164.90	
Number of Observations	340,580	
Number of Significant Variables	57	
% Change in Odds = (Odds Ratio – 1) * 100		
*Significant at the 90% confidence level (based on a two-tail test) **Significant at the 95% confidence level (based on a two-tail test) ****Significant at the 99% or greater confidence level (based on a two-tail test)		

This chapter discussed several methods of regression analysis to answer the questions posed in this study. Multicollinearity and heteroskedasticity issues appeared in the data but were corrected using robust standard errors. The final pseudo R^2 of 0.2893 indicates that the independent variables accounts for 28.93% of the variance in life satisfaction, which is a good fit, considering the model does not include personality factors that could explain 50% of the variance in happiness. Overall, 36 of the 43 significant variables are significant at the 99% or greater confidence level. The results confirmed my hypothesis as most of my key explanatory variables have effects that were significant. The logistic regression result shows that compared to individuals who have health insurance coverage, those with no health insurance coverage are 9.4% less likely to be satisfied with life, which is statistically significant at the 99.9% confidence level. More alarmingly, those who could not see a doctor due to cost any time in the past 12 months are 40.7% less likely to be satisfied with life, also significant at the 99.9% confidence level. More interestingly are the interaction effects of the Medicaid variables, which will be discussed more in-depth in the following chapter. In the next chapter, I will evaluate this study's research question and discuss policy implications of my findings, and strategies to improve the well-being of uninsured individuals.

Chapter Five

CONCLUSION

The purpose of this study has been to explore the connection between happiness and health insurance coverage, as well as health care cost and Medicaid rankings. In chapter one, I provided the framework for my research question by discussing the lack of health insurance coverage, rising health care costs, and their relationship to declining health status, as well as the robust relationship between health and well-being. I suggested a possible relationship between health insurance coverage and well-being. Existing well-being research focused on the effect of income and health on happiness; however, few if any existing studies focus on the impact of health insurance coverage and health care cost on happiness, despite the fact that they are the prevalent focus of current policy issues.

This study fills the gap by using regression analyses to find empirical evidence of the probable relationship between health insurance coverage and happiness. In chapter two, I examined the current literature on well-being and the major predictors of happiness. My review confirmed the gap in the existing literature and demonstrated the necessity to conduct this study. In chapter three, I explained the regression analysis model and the theoretical framework I used to test my hypothesis. In chapter four, I discussed the regression analyses used to analyze data from the CDC's BRFSS survey and statewide Medicaid rankings from Ramírez de Arellano & Wolfe's study. In this final chapter, I summarize the empirical findings of the regression analysis and examine how it answers my research question. Additionally, I discuss the policy implications of key findings from my study. Finally, I conclude with a discussion of the study's limitations, followed by suggestions for future research.

Empirical Findings

My regression analysis produced 43 significant well-being predictors, of which 36 are significant at the 99% or greater confidence level. Table 5.1 and 5.2 below provide the odds ratio at the 90% confidence intervals, and the percent change in odds for each unit increase in the independent variable for both dichotomous and continuous variables, listed in order from highest to lowest. Table 5.1 displays the odds ratio and confidence intervals of significant dichotomous variables while Table 5.2 displays the odds ratio and confidence intervals for continuous variables, which also includes the percent change in odds for standard deviation increase in the independent variable.

Table 5.1: Odds Ratios and Confidence Intervals of Significant Dichotomous Variables

Variable Name	Odds Ratio Exp(β)	90% Confidence Interval Lower Bound	90% Confidence Interval Upper Bound	% Change in Odds of being Happy for Unit Increase in Independent Variable
DICHOTOMOUS VARIABLES				
Excellent Health (relative to Poor Health)	4.5638*** (0.2167)	4.2208	4.9346	356.4%
Very Good Health (relative to Poor Health)	3.2881*** (0.1232)	3.0915	3.4973	228.8%
Good Health (relative to Poor Health)	2.3338*** (0.0764)	2.2114	2.4630	133.4%
Married (relative to Never Married)	2.1803*** (0.0626)	2.0797	2.2858	118%
Unemployed >1 Year (relative to Employed)	0.4580*** (0.0166)	0.4314	0.4862	-54.2%
Income <$10k (relative to Income >$75k)	0.4735*** (0.0207)	0.4406	0.5090	-52.6%
Unemployed <1 Year (relative to Employed)	0.4868*** (0.0193)	0.4559	0.5197	-51.3%
Fair Health (relative to Poor Health)	1.5134*** (0.0429)	1.4444	1.5857	51.3%
Unmarried Couple (relative to Never Married)	1.5055*** (0.0847)	1.3723	1.6516	50.6%
Income $10k to <$15k (relative to Income >$75k)	0.5048*** (0.0216)	0.4703	0.5417	-49.5%

Variable Name	**Odds Ratio Exp(β)**	**90% Confidence Interval Lower Bound**	**90% Confidence Interval Upper Bound**	**% Change in Odds of being Happy for Unit Increase in Independent Variable**
Income $15k to <$20k (relative to Income >$75k)	0.5335*** (0.0229)	0.4970	0.5727	-46.6%
Income $20k to <$25k (relative to Income >$75k)	0.5525*** (0.0219)	0.5176	0.5897	-44.7%
Hispanic (relative to White)	1.4404*** (0.0541)	1.3540	1.5323	44.0%
American Indian (relative to White)	1.4298*** (0.0938)	1.2836	1.5928	43.0%
Cannot Afford Doctor	0.5928*** (0.0131)	0.5717	0.6148	-40.7%
College Graduate (relative to Never Attended School and Elementary)	0.6145*** (0.0326)	0.5631	0.6706	-38.5%
Income $25k to <$35k (relative to Income >$75k)	0.6203*** (0.0240)	0.5820	0.6611	-38.0%
Widowed (relative to Never Married)	1.3670*** (0.0508)	1.2860	1.4532	36.7%
Some College (relative to Never Attended School and Elementary)	0.6565*** (0.0337)	0.6000	0.7188	-34.3%
Income $35k to <$50k (relative to Income >$75k)	0.6628*** (0.0247)	0.6033	0.7144	-33.6%
Having Three Children	1.3133*** (0.0657)	1.2095	1.4260	31.3%
Unable to Work (relative to Employed)	0.6951*** (0.0212)	0.6611	0.7309	-30.5%
Having Five or more Children	1.2699** (0.1394)	1.0601	1.5213	27.0%
Female	1.2673*** (0.0240)	1.2283	1.3076	26.7%
African American (relative to White)	1.2367*** (0.0379)	1.1757	1.3008	23.7%
Asian (relative to White)	1.2302** (0.1060)	1.0676	1.4177	23.0%
High School (relative to Never Attended School and Elementary)	0.7777*** (0.0393)	0.7157	0.8452	-22.2%
Income $50k to <$75k (relative to Income >$75k)	0.7978*** (0.0304)	0.7493	0.8495	-20.2%
Retired (relative to Employed)	1.2009*** (0.0383)	1.1393	1.2657	20.1%
Having Two Children	1.1903*** (0.0410)	1.1246	1.2598	19.0%
Some High School (relative to	0.8533***	0.7786	0.9351	-14.7%

Variable Name	Odds Ratio Exp(β)	90% Confidence Interval Lower Bound	90% Confidence Interval Upper Bound	% Change in Odds of being Happy for Unit Increase in Independent Variable
Never Attended School and Elementary)	(0.0475)			
Having Four Children	1.1466* (0.0871)	1.0119	1.2993	14.7%
Multi Racial (relative to White)	1.1013* (0.0603)	1.0064	1.2053	10.1%
No Health Insurance Coverage	0.9061*** (0.0237)	0.8678	0.9460	-9.4%
Divorced (relative to Never Married)	1.0895*** (0.0314)	1.0390	1.1424	9.0%
Separated (relative to Never Married)	0.9238* (0.0422)	0.8570	0.9959	-7.6%
Having One Child	1.0615** (0.0312)	1.0113	1.1142	6.2%
*Significant at the 90% confidence level (based on a two-tail test) **Significant at the 95% confidence level (based on a two-tail test) ****Significant at the 99% or greater confidence level (based on a two-tail test)				

Table 5.2: Odds Ratios and Confidence Intervals of Significant Continuous Variables

Variable Name	Odds Ratio Exp(β)	90% Confidence Interval Lower Bound	90% Confidence Interval Upper Bound	% Change in Odds of being Happy for Unit Increase in Independent Variable	% Change in Odds of being Happy for Standard Deviation Increase in Independent Variable
CONTINUOUS VARIABLES					
Days of Poor Mental Health in 1 Month	0.9284*** (0.0007)	0.9272	0.9296	-7.2%	-43.6%
Days w/ Not Enough Sleep	0.9759*** (0.0007)	0.9746	0.9772	-2.4%	-21.5%
Percent Medicaid Scope of Services for State	0.5838*** (0.0587)	0.4947	0.6888	-41.6%	-6.1%
Age	1.0024** (0.0009)	1.0009	1.0039	0.2%	3.9%
Days of Poor Physical Health in 1 Month	0.9963*** (0.0010)	0.9946	0.9980	-0.4%	-3.2%

Variable Name	Odds Ratio Exp(β)	90% Confidence Interval Lower Bound	90% Confidence Interval Upper Bound	% Change in Odds of being Happy for Unit Increase in Independent Variable	% Change in Odds of being Happy for Standard Deviation Increase in Independent Variable
Percent Medicaid Eligibility for State	0.8526** (0.0637)	0.7539	0.9642	-14.7%	-2.5%
*Significant at the 90% confidence level (based on a two-tail test) **Significant at the 95% confidence level (based on a two-tail test) ****Significant at the 99% or greater confidence level (based on a two-tail test)					

While the intention of the regression analysis was to show how different variables impact happiness and well-being levels by holding other explanatory variables constant, it is important to note that the results do not prove causation, but do imply it. Thus, the results can be understood in terms of having a certain characteristic described in the independent variable merely decreases or increases the odds of being happy rather than causing happiness. As shown above, the odds ratio demonstrates the increased likelihood that the dependent variable will equal one (i.e. satisfied or very satisfied with life) given a one-unit change in an independent variable while holding all other variables in the equation constant.

Key Explanatory Variables

The data suggest that the odds of being satisfied with life are 40.7% lower for individuals who could not see a doctor due to cost. When this variable is interacted with various income levels, the data show that individuals with household income between $15,000 and $75,000 who could not see a doctor due to cost, have 13% to 23%lower odds of being satisfied with life. Even more surprising is the effect of the interaction between individuals who cannot afford a doctor and health status. The data suggests that an excellent health status increases the odds of being satisfied with life by 356% while very good health increases the odds of life satisfaction by 229%. However, when these health factors are interacted with the variable not being able to see a doctor due to cost, the likelihood of happiness is lowered by 35% when interacting with excellent health and 28% when interacting with very good health. Similarly, individuals without health insurance coverage have 9.4% lower odds of being happy. When interacting this variable with excellent health and very good health, the odds of life satisfaction is decreased by 31% and 16%, respectively. This suggests that even for individuals with excellent and very good health, the negative effect of not having health insurance or not being able to see a doctor due to cost reduces the substantial positive effect of their health status.

Regarding the Medicaid variables, the data shows that individuals residing in states with a 1-standard-deviation-higher percentage of Medicaid scope of services ranking have 6.1% lower odds of being satisfied with life. Likewise, individuals residing in states with a 1-standard-deviation-higher percentage of Medicaid eligibility ranking have 2.5% lower odds of being satisfied with life. However, individuals who are self-employed and residing in states with higher Medicaid quality of care ranking have 56% higher odds of being satisfied with life. Similarly, respondents who have been unemployed for more than one year that reside in states with higher Medicaid quality of care ranking have 51% higher odds of being happy. Also, when Medicaid quality of care ranking is interacted with household income between $10,000 and $15,000, it yields a positive outcome of 45% higher odds of being happy. The same phenomenon is observed for individuals with household income between $20,000 and $25,000 residing in states with high Medicaid reimbursement ranking, which yields a 39% higher likelihood of being satisfied with life.

Health

Not surprisingly, my data reveal evidence that health status is one of the strongest predictors of life satisfaction, which is consistent with findings of other research on well-being. When using poor health as a reference, individuals with excellent health status have the strongest happiness predictors, as they are 356% more likely to be satisfied with life. Next to excellent health status, very good health is the strongest happiness predictor as it increases the odds of happiness by 229.8%. Those with good health and fair health status are 133.4% and 51.3% more likely to be satisfied with life. Similarly, each day of poor mental health decreases the odds of life satisfaction by 7.2%, which translates to 216% lower odds of happiness for 30 days of poor mental health. Likewise, each day that an individual did not get enough sleep lowers the odds of life satisfaction by 2.4%, thus can decrease the likelihood of life satisfaction by 72% for 30 days of lack of sleep. In addition, each day of poor physical health reduces the odds of life satisfaction by 0.4%, up to 12% lower odds of happiness for 30 days of poor physical health in one month.

Research Question Evaluation

This study seeks to answer the following research questions: (1) what is the impact of health insurance coverage and health care cost on happiness and well-being? and (2) what is the impact of Medicaid benefits on well-being, and in particular, is the impact greater for low-income individuals living in states with more generous Medicaid benefits? Using regression analysis to analyze the BRFSS survey, my research indicates that health insurance coverage and health care cost have a strong and statistically significant impact on well-being, at the 99.99% confidence level. Not having health insurance coverage decreases a person's likelihood of life satisfaction by 9.4%. When the lack of insurance coverage is interacted with excellent and very good health status, the likelihood of life satisfaction decreased by 31% and 16%, respectively. This is quite surprising because despite excellent health and very good health's immense effect on increasing the likelihood of being happy by 356% and 229%, their positive effect on happiness is significantly reduced when these individuals lacked health insurance coverage. The data suggest that health insurance coverage affects a person's well-being regardless of health status, as having excellent and good health does not buffer people from unhappiness. The psychological and financial worries associated with not having health insurance seem to overwhelmingly overshadow the positive effect of good health.

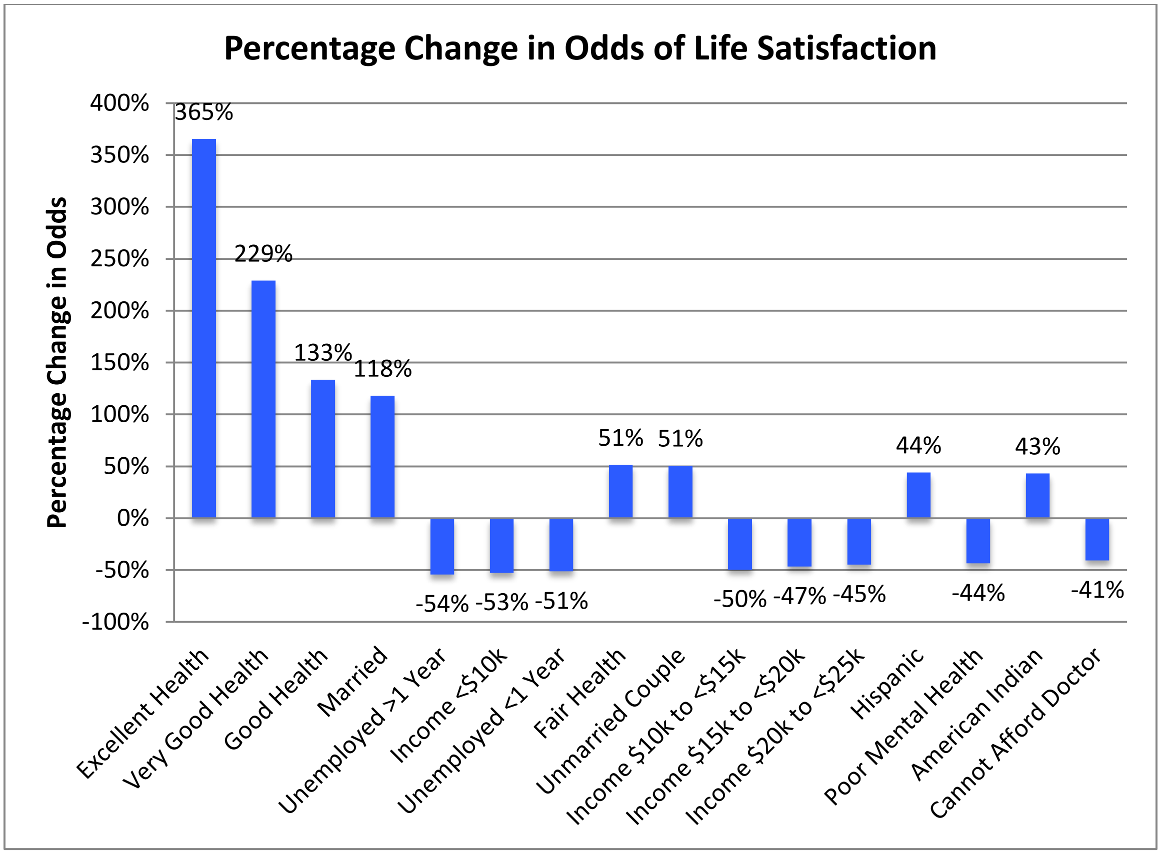
Similarly, individuals who could not see a doctor due to cost are 40.7% less likely to be satisfied with life. Since not being able to see a doctor due to cost is a measure of the ability to pay for health care cost, the data suggests there is a strong relationship between health care cost and happiness. The impact of this effect on life satisfaction is much greater than not having health insurance coverage. However, there is some overlap between these two measurements as they are somewhat related to each other. For example, not being able to see a doctor due to cost also implies that the individual may not have health insurance, or have such limited health insurance coverage that the co-payments are more than what the individual could afford. When the variable not being able to see a doctor due to cost is interacted with various income levels, the data indicates that individuals with household income between $25,000 and $75,000 are 13.4% to 23.1% less likely to be satisfied with life. Since there is an extensive spread of income effect ranging from $25,000 to $75,000, this suggests that the inability to pay for a doctor significantly decreases an individual’s likelihood of happiness regardless of income levels. Furthermore, the negative effect on happiness of not being able to see a doctor due to cost is almost equivalent to the effect of having poor mental health or being unemployed for less than one year. This is an important finding as it further stresses the substantial impact of health care cost on happiness.

My regression analysis reveals that Medicaid measures such as the percentage of Medicaid scope of services and Medicaid eligibility rankings actually lower the likelihood of satisfaction rather than increase it. Specifically, individuals residing in states with a 1-standard-deviation-higher percentage of Medicaid scope of services ranking are 6.1% less likely to be happy while those residing in states with a 1-standard-deviation-higher percentage of Medicaid eligibility ranking are 2.5% less likely to be happy. Initially, I found these findings somewhat perplexing, as one would expect that individuals residing in states with more generous Medicaid eligibility and Medicaid scope of services rankings would more likely to be satisfied with life. However, further analysis of this scenario reveals several likely explanations for this negative outcome. Firstly, individuals residing in states with more generous Medicaid benefits may be required to pay higher tax to fund these social programs. Secondly, the Medicaid variables are capturing other states effects that may not be associated with Medicaid programs (e.g. state economy, job prospects, unemployment, social programs). Thirdly, Medicaid rankings may be somewhat subjective since they are sensitive to the criteria set forth by the researchers given limited information and efforts to compare Medicaid rankings on such a broad scale. Thus, the Medicaid rankings may not necessarily reflect actual Medicaid benefits. Lastly, the individual's perception of Medicaid generosity is subjective and relative to that individual's comparison group, which may not be a true representation of actual benefits.

Furthermore, when interacting the percent of Medicaid quality ranking with other variables such as self-employment, unemployment, and low-income groups, the Medicaid quality ranking variable became significant at 98% confidence and yielded a positive percent change in odds ratio. Likewise, when Medicaid measures are combined with the lowest income groups and individuals who are either self-employed, or unemployed for greater than one year, the likelihood of life satisfaction increases substantially, ranging from 39 to 56% increase. This implies that although individuals residing in states with more generous Medicaid benefits are less likely to be happy, individuals living in those states in the lowest income groups that typically qualify for Medicaid, self-employed and unemployed individuals who may not qualify for employer-sponsored health benefits are considerably more likely to be happy. This makes sense since these individuals benefit directly from more generous Medicaid benefits, whereas the general population is less likely to be happy as they may be required to absorb the extra tax burden associated with more generous Medicaid benefits.

The findings of this analysis add to the existing literature by suggesting that having health insurance coverage, being able to afford a doctor, and residency in states with more generous Medicaid benefits substantially impact an individual's well-being. Furthermore, the regression results reveal that the negative effect of not being able to see a doctor due to cost is nearly comparable to the effect of the difference between being in the third lowest income group and having income greater than $75,000. This finding is consistent with findings from Blanchflower's (2009) study, which found that the size effect of not being able to see a doctor due to cost is the same as the difference between having zero income and income of $75,000 or more or between working as an employee and having been unemployed for at least twelve months. Figure 5.1 below displays an illustration of the percentage change in odds of life satisfaction by major causal factors.

Figure 5.1: Percentage Change in Odds of Life Satisfaction by Major Causal Factors



Policy Implications

For nearly 45 years, the Medicaid program has grown to become the nation's primary publicly funded health coverage program and safety net for millions of Americans who would otherwise remain uninsured. Under the ACA, Medicaid will be expanded to nearly everyone under age 65 with income up to 133% of the FPL by 2014. The findings in this study underscore the detrimental impact of lack of health insurance coverage, and thus further substantiate the need for the ACA's Medicaid expansion and the creation of the health insurance exchange to make affordable health care a reality for all Americans. Evident in this study is the critical need to make health insurance more affordable for the average working family that does not qualify for Medicaid but cannot afford health insurance. The data demonstrate that having high-income does not seem to protect individuals from the negative consequences of high health care cost, as high health care cost can quickly exhaust household savings regardless of income level.

Through various interaction variables introduced in my regression model, my study demonstrates that the negative effects of high health care costs and lack of insurance coverage on happiness is substantial, even for individuals with excellent health and high income. This suggests that excellent health status and high income do not buffer people from unhappiness as the negative effects of high health care cost and lack of health insurance coverage reduces the positive effects of good health and high income. Specifically, the uncertainty of not having health insurance and the inability to afford needed health care can bring other psychological and financial worries as individuals can quickly exhaust their savings and incur debt in the event of required major medical procedures, given such high out of pocket costs for those without health insurance. The consequences of the lack of health insurance extend beyond the health and productivity impact on the individual since lack of health insurance also directly impacts their families, communities, and society at large. Thus, everyone shares the risks of lack of health insurance. To promote stability and avert unnecessary risks of working families living in constant fear, individuals need to be able to purchase affordable health insurance for themselves and their families. Having a venue to obtain cost-effective routine and preventive care and screenings could protect individuals from potentially detrimental but preventable health consequences that often incur costs borne largely by the public.

Being such an integral part of our health care system, Medicaid's significant role for the poor and those not offered employer-sponsored health insurance (the unemployed and self-employed) is also evident in this study. Specifically, the data reveal that although individuals living in states with more generous Medicaid benefits are less likely to be happy, individuals who are low-income, unemployed, and self-employed living in these states are much more likely to be happy. This outcome could be explained by the assumption that the general population residing in states with high Medicaid benefits is less likely to be happy due to the additional tax burden to pay for Medicaid programs, whereas low-income, unemployed, and self-employed individuals are more likely to be happy as they may be direct recipients of Medicaid benefits. Without Medicaid programs, these individuals may remain uninsured given their low-income status and lower likelihood of being offered employer sponsored health insurance. Moreover, next to health and marital status, employment status is the third most influential predictor as it significantly impacts an individual's likelihood of happiness. Unfortunately, since health insurance is often tied to an individual's employment, losing a job often means losing health insurance coverage, disruption in health care services, and possibly diminished health for the unemployed individuals and their families. Besides other financial and psychological factors associated with unemployment, sudden breaks in medical services at a time when access to health care services such as mental health may be needed most could impose unfavorable effects on an individual's well-being. Overall, these findings validate the need for Medicaid expansion to reach more Americans in need of health insurance. For those with income above the eligibility cut off, having a venue to purchase affordable health insurance will ensure continued care for themselves and their families.

Consistent with findings from other well-being research, this study finds that health status is by far the most influential predictor of well-being. Having excellent health increases an individual's chances of happiness approximately three times the effect of the next strongest predictor, marital status. Most astounding is health's effect on happiness compared to the income effect, since health's effect on happiness is almost seven times greater than the effect of income on happiness. This finding emphasizes the serious need to improve health care access to advance public policy that improves the well-being of all Americans, which is arguably more pressing than raising the nation's GDP. This study provides evidence that the most effective strategy to improve well-being is through improving health outcomes, therefore health should be a high priority policy agenda. Lack of health insurance significantly decreases an individual's access to screenings and routine, preventive, and acute care, which could increase the severity of illness and lead to premature death. Thus, increasing access to health care, improved health care quality and delivery are among the most effective ways to improve individuals' health conditions and decrease disparities and inequity in access to health care.

Moreover, this study reveals the significant impact of mental health on individuals' happiness, which is consistent with findings from other well-being studies. Each day of poor mental health decreases an individual's odds of life satisfaction by 7.2%, or up to 216% lower odds of happiness for 30 days of poor mental health. Despite its significant impact, mental health problems continue to be neglected and underestimated, while mental health resources are much more likely to be under allocated in communities across the U.S. Despite its widespread impact on countless aspects of a person's life and its impact on a large number of individuals, only 25% of people with mental illness are treated, compared to 75% of those with physical conditions (Earth Institute, 2012). While its impact on happiness is substantial, low mental health also affects other important life aspects, such as earnings, employment status, criminal records, teenage pregnancy, physical health, homelessness, and education performance (Earth Institute, 2012). Thus, policymakers should recognize the severity and prevalence of mental health problems in pursuit of an agenda that warrants adequate funding and resource allocation toward health care programs aimed at addressing societal mental health problems. In addition to other pressing policy implications, not addressing this issue could intensify the low likelihood of happiness and well-being for mentally ill individuals.

According to the CBO, the ACA will result in 32 million Americans gaining health insurance by 2019. The remaining uninsured will be comprised of undocumented immigrants who are not eligible for benefits, those exempted from the mandate because insurance is not affordable, and those who choose to forgo insurance and pay the mandate penalty. Since the ACA excludes undocumented immigrants from all of its programs aimed to help reduce the uninsured rate, undocumented immigrants will not be eligible for public insurance or any type of private coverage obtained through the health exchange. As such, undocumented immigrants will emerge as an even larger share of the uninsured population. Next to the largest group of individuals who qualify for Medicaid but remain unenrolled, undocumented immigrants are projected to become the second-largest group among the uninsured (Clemans-Cope et al., 2012). Currently, 19% of the uninsured in California are undocumented immigrants, compared to the national average of 10%. Even with health reform, it is estimated that 1.24 million undocumented Californians will remain uninsured.

Given the sizeable undocumented immigrant population in California that will be left out of the health exchange, California faces a greater responsibility than any other state in seeking strategies to mitigate this population's high uninsured rate and address undocumented immigrants' access to affordable health care for the long term. Increased health care access could raise immediate costs but avert considerable long-term costs associated with emergency care treatments that would otherwise be compensated by the community and society at large. With such significant findings on the impact of health insurance coverage, health care cost, and health status on happiness, the likelihood of happiness for undocumented immigrants is disheartening, given such disparities in health insurance coverage for this population. Admittedly, this problem will not be resolved without broader reform of immigration policy that includes either a path toward citizenship or at a minimum, the elimination of barriers to participate in programs offered through the ACA.

To mitigate the detrimental impact of lack of insurance coverage and high health care cost, policymakers should consider strategies to address challenges that will accompany the ACA. These challenges include, but not limited to, outreach to individuals who would remain uninsured even after the ACA implementation, simplifying Medicaid enrollment process, and improving Medicaid access and quality of care. Given that Medicaid is our nation's main publicly financed health coverage program for low-income Americans and given existing shortages and low provider participation in Medicaid, expanded Medicaid coverage will place additional pressure on access to quality care. As such, competitive compensation may be needed to incentivize providers' participation in Medicaid programs. Thus, having adequate health care resources to respond to anticipated demand for health care services will likely increase the probability of successful implementation of these provisions in the ACA.

Similar to findings from other well-being research, this study finds many non-income predictors are much more effective at predicting well-being than income measures alone. Since health's predictive effect on happiness is seven times that of income, the need to place less emphasis on income measures in assessing societal well-being level is increasingly evident. Given that other countries are tracking and incorporating well-being measures into their policy decision making process, perhaps it is time for the U.S. to follow their lead in creating our own SWB measures to help drive policies. A deeper understanding of well-being and happiness can inform economic policy decisions and provide a broader and richer research foundation for policy strategy. Happiness research may provide policymakers meaningful opportunities to extend understanding of well-being beyond the economic factors that have been traditionally used. Well-being data can facilitate improved policy decisions, feedback, and potential for further improvement. If, according to Bok (2012), depression, lack of sleep, chronic pain, lack of health care, and financial worries are among the top problems that threaten individuals' well-being, incorporating strategies to address these problems could effectively increase our society's overall well-being. In the end, we learn that income does not matter as much compared to other non-income factors, such as health, marital, and employment status. This study offers some insight about the relevant factors that are effective in predicting individual happiness and well-being, while highlighting aspects of health that are often ignored, particularly the roles of health insurance, health care cost, and Medicaid.

Limitations of the Study and Future Research

The complexity of health insurance coverage and health care cost on happiness and well-being is extensive and multifaceted. Many possibilities exist for future research to further explore the effect of health insurance coverage and health care cost on happiness. Given that this study is among only a few to examine this aspect of happiness, it has several limitations that could be addressed in future studies. One limitation includes coding the dependent variable, life satisfaction, into a dichotomous variable with zero and one, in which one represents the presence of life satisfaction and zero represents its absence. This greatly limits the type of suitable regression analysis to only logistic regression. Future studies could recode this variable into categorical or hierarchy of life satisfaction levels to take advantage of other types of regression analyses available, such as OLS regression with linear-linear, linear-linear quadratic, log-linear, and log-semilog functional forms, or ordered logit and probit regressions. Given the dichotomous dependent variable and the inclusion of various health measures in my regression model, my study's results cannot be compared directly with Blanchflower's study. When reviewing Blanchflower's study, I noticed that health variables are missing from the study's regression models. However, it is likely that failing to include health measures would lead to omitted variable bias that incorrectly leaves out the important health factors found to be so significant in other well-being studies. This bias could compensate for the missing factors by overestimating or underestimating the effect of other factors in the regression model.

To limit the scope of this study, I only used one year of data from the BRFSS survey. Expanding this study to include multiple years will allow for a comparison of results across multiple years. This will isolate the effect of health insurance coverage and health care cost to determine whether the findings are consistent over time. Moreover, because I relied solely on using secondary data sources for my study, I was limited to the variables the survey contained. As a result, I was not able to study the effect of various types of health insurance on happiness. Future studies could use a different data source that includes this health insurance variable to study whether individuals having public health insurance are less happy than those receiving private health insurance. Given the tremendous impact of genetics and personality, finding a data source that contains these measures could significantly increase the overall model fit and regression estimates. Moreover, to determine whether these impacts hold across multiple measurements of happiness, future researchers should consider exploring the effect of health insurance coverage and health care cost by using happiness data sources that contain other instruments to measure happiness. Although not possible to study at this time, studying the long-term effect of the ACA on well-being and happiness would be helpful in the evaluation of the ACA's impact on well-being. Future studies could consider comparing the effect of health insurance coverage and health care cost on happiness before and after the ACA implementation.

Final Thoughts

This study highlights the importance of health insurance coverage and health care cost on happiness and emphasizes their significant roles in the measurement of well-being. The findings from this study demonstrate that the impact of the lack of health insurance coverage is not limited to poorer health outcomes, increased financial burden to the 48 million uninsured individuals and their families, and negative externalities to the communities and society. In addition, lack of health insurance coverage and high health care cost also imposed another hidden cost to the uninsured individuals: lowered likelihood of happiness and well-being. These findings add to the existing literature by suggesting that having health insurance coverage, being able to see a doctor, and residency in states with better Medicaid rankings substantially impact an individual's well-being. Moreover, these effects held across income categories and health status, which further validate their significant influence on happiness. The implication is that policymakers should consider strategies aimed at improving individuals' access to quality health care to bridge the disproportionate gap of health care access among low-income, minorities, and non-elderly individuals.

Although the Declaration of Independence promises every American the unalienable rights to life, liberty, and the pursuit of happiness, we can extrapolate from this study that not every American has the opportunity to pursue happiness, particularly those with poor health, those without health insurance coverage, the unemployed, and those who cannot afford a doctor. Overwhelmingly, my research reveals that health is the strongest predictor of happiness, seven times that of income indicators. This demonstrates that to effectively improve the well-being of individuals, policymakers should place less emphasis on increasing GDP and rather focus more on ensuring not only increased access to health care services, but also quality and continuity of care for all Americans. Efforts to increase the number of individuals with health insurance such as the ACA have the potential to improve the well-being of many Americans.

Appendix A: Table of Literature Study Methods, Data Sets, Findings, and Significance

Author, Publication Date, Title	Methodology & Variables	Population & Sample Size	Results and Limitations
REGRESSION-BASED STUDIES			
The Earth Institute, World Happiness Report.	Regression Analysis	Gallup World Poll (GWP), World Values Survey (WVS), European Values Survey (EVS), European Social Survey (ESS), 2005-2011, British Cohort Study, BHPS, GSOEP, WVS	The impact of severe disability is estimated as being 0.6 points on a one to seven life satisfaction scale, and that of moderate disability as 0.4 points. Adaption to disability is estimated at around 50% for moderate disability and 30% for severe disability (around one-third of the life-satisfaction effect of the latter dissipates over time) Cross-sectional regression: excellent health increases life satisfaction score by 3.45 points on the GSOEP (0-10), 1.94 points on BHPS (1-7), 2.69 points on WVS (1-10), good health increases life satisfaction score by 2.82 points on GSOEP, 1.59 points on BHPS, 2.06 points on WVS, satisfactory health increases life satisfaction score by 2.04 points on GSOEP, 10.9 points on BHPS, 1.44 points on WVS, poor health increases life satisfaction score by 1.26 points (GSOEP), 0.59 (BHPS), 0.61 (WVS).
Binder, M. & Coad, A. (2011). From average Joe's happiness to miserable Jane and cheerful John: using quantile regressions to analyze the full subjective well-being distribution.	OLS regression & Quantile regression (calculating coefficient estimates at various quantiles of the conditional happiness distribution) Seven point Likert	British Household Panel Survey (BHPS) – longitudinal survey of private households in Great Britain, 2006 wave of the data set, N=11,591.	Observed a decreasing importance of income, health status and social factors with increasing quantiles of happiness. Income, health, social relations have strongest impact for the least happy individuals. Health is associated with life satisfaction more strongly in the lower quantiles similar to income. Health accounts for 0.196-point increase in life satisfaction, social relations account for 0.387-point increase in life

Author, Publication Date, Title	Methodology & Variables	Population & Sample Size	Results and Limitations
	scale, ranging from "not satisfied at all" (1) to "completely satisfied" (7).		satisfaction (significant at 1%). Quantile regression: At the median (50% quantile) social (0.391 point), health (0.203 point), log income (0.069) with significance at 1%) At the median (50% quantile) one standard deviation of the health variable would be associated with an increase in life satisfaction of 0.27 (27%), significant at 1%. At 10% quantile, one standard deviation of the health variable would be associated with an increase in life satisfaction of 0.416 (41.6%), significant at 1%. A 25% quantile= 0.337, 75% quantile 0.22, 90% quantile =0.155.
Bottan, N. & Truglia, R. (2011). Deconstructing the hedonic treadmill: is happiness autoregressive?	Regression Analysis	German Socio-Economic Panel Study (GSOEP) – 22 panel lengths Japanese Panel Survey of Consumers (JPSC) – 14 panel lengths British Household Panel Survey (BHPS) – 10 panel lengths Swiss Household Panel (SHP) – 8 panel lengths	Reported happiness bounces back completely after two years of losing a spouse. Adaptation to unemployment is 72% after 2 years. Similar pattern for marriage, divorce, childbirth, and other events were found.
Oswald, A. & Wu, S. (2010). Objective confirmation of subjective measures of human well-being: evidence from the U.S.A.	Regression – Linear Ordinary Least Squares estimator; ordered estimator to allow coefficients to be read off as cardinal	2005-2008 Behavioral Risk Factor Surveillance System (N= 1.3 million U.S. inhabitants between 18 and 85 years old). Life satisfaction is coded for	Across America, people's answers trace out the same pattern of quality of life as previously estimated, from solely non-subjective data. R-square is 0.36, meaning 36% of the variance in the y-axis variable is explained by the x-axis variable. Correlation of regression-adjusted life

Author, Publication Date, Title	Methodology & Variables	Population & Sample Size	Results and Limitations
	life-satisfaction points.	each individual from a score of 4 (very satisfied) to 1 (very dissatisfied)	satisfaction and objective quality-of-life ranking is 0.598. This suggests that subjective well-being data contain genuine information about the quality of human lives.
Salinas-Jimenez, M., Artes, J. & Salinas-Jimenez, J. (2010). Income, Motivation, and Satisfaction with Life: an Empirical Analysis	Regression Analysis	World Values Survey (WVS) 2005-06 – individuals from 10 developed countries (Australia, Britain, France, Germany, Italy, Japan, Netherlands, Spain, Sweden, and U.S.A.) N=10,800, 10-point life satisfaction scale	Higher coefficients are obtained as subjective health moves from fair to good or very good health. As expected, enjoying better health has a significant positive effect on life satisfaction. Fair health increases life satisfaction by 0.64 point, good health increases life satisfaction by 1.09, and very good health increases satisfaction by 1.62 point. Being married increases life satisfaction by 0.302, while being unemployed decreased life satisfaction by 0.24. Middle income and rich income increase satisfaction by 0.176 and 0.212.
Sharpe, A., Ghanghro, A. & Johnson, E. (2010). Does money matter? Determining the Happiness of Canadians	Regression Analysis Variables: individual and societal variables	N=70,192 Canadian Community Health Survey (CCHS) 2007-08	A one-unit increase from the average of perceived mental health increases the proportion of individuals satisfied with life by 17.5 % points. A one-unit increase in mental health on happiness is equivalent to the effect of a 209% increase in household income. One-unit increase in health status is equivalent to a 155 % increase in household income on happiness. One-unit increase in stress level is equal to the effect of a 140% decrease in household income on happiness. One unit increase in sense of belonging is equal to a 114% increase in income from the average person.
Angner, E., Miller, M., Ray, M., Saag, K., & Allison, J.	Multivariable logistic regression	N=383 recruited from the practice of 39 primary-	Lowest-quartile happiness was associated with poverty, unfavorable self-rated health and lower

Author, Publication Date, Title	Methodology & Variables	Population & Sample Size	Results and Limitations
(2009). Health Literacy and Happiness: a community-based study.		care physicians from 21 of Alabama's 67 counties (50 years or older).	health literacy. Inadequate health literacy may be an obstacle to happiness above and beyond its effect on poverty and health. For those with unfavorable (poor or fair) self-rated health, the odds of having lower-quartile happiness is 4.16 times more than those with favorable self-rated health (significant at $p<0.05$), this is the highest predictor, with poverty at 3.16, health literacy (lower) at 3.04, and college education (none) at 2.07.
Blanchflower, D. (2009) Happiness and Health Care Coverage (working paper)	Regression analysis – Ordinary Least Squares	Behavioral Risk Factor Surveillance System (BRFSS) – phone survey undertaken in the U.S. from 2005-2009	Found evidence that not having the ability to see a doctor because of an inability to pay is a major and substantial source of unhappiness in the U.S., even for those with high income. Not being able to see a doctor due to cost on happiness equals a 21-percentage point decrease in happiness. This magnitude is equivalent to the difference between zero income and income of greater than $75,000 or between being employed and having been unemployed for at least twelve months.
Mello, L. & Tiongson, E. (2009). What is the value of (my and my family's) good health?	OLS regression, ordered logit and probit & Alternative (life satisfaction) methodology similar to a cost-benefit analysis in health care	U.S. General Social Survey (GSS) 1972-2006, approximately 3,000-4,500 individuals are interviewed in each wave.	The estimated compensating value of one's own poor health (up to $128,000) is high and approximately 60 to 1,000% of the sample's mean income. These compensating values are comparable to estimates of the statistical value of a life year in perfect health. Tolley et al. (1994) show that the monetary value of a year in perfect health falls somewhere between $90,000 and $420,000 in 2000 prices. General health status accounts for 0.33 point

Author, Publication Date, Title	Methodology & Variables	Population & Sample Size	Results and Limitations
			increase in happiness using OLS regression. When general health status is replaced by five specific types of health conditions (general illness, mental health, infertility, alcoholism, use of illegal drugs), mental health accounts for 0.292 point decrease in happiness, alcoholism decreases 0.371 point in happiness, and 0.294 point (significant at 1%). General illness did not yield significant result.
Blanchflower, D. & Oswald, A. (2007). Hypertension and Happiness across Nations.	Pearson and Spearman tests, Ordinary Least Squares and Ordered Logit methods	Eurobarometer #56.1 data set collected in September and October 2001 from approximately 15,000 randomly sampled individuals in 16 countries (Denmark, West Germany, Greece, Italy, Spain, France, Ireland, Luxembourg, the Netherlands, Portugal, the United Kingdom, East Germany, Finland, Sweden, Austria, and Belgium)	Happier nations also report systematically lower levels of hypertension. Blood-pressure readings might be valuable as part of a national well-being index. There is evidence of inverse relationship between national subjective well-being and national blood-pressure problems. Happier nations report fewer blood-pressure problems.
Abdel-Khalek, A. (2006) Happiness, health, and religiosity: significant relations.	Multiple regression	N=2210 (1,056 male and 1,154 female) volunteer Kuwaiti Muslim undergraduates	The main predictor of happiness was mental health. Mental health accounted for 60% of the variance in predicting happiness, while religiosity accounted for around 15% of the variance in predicting happiness. Self-rating of physical health did not contribute significantly to the prediction of happiness.

Author, Publication Date, Title	Methodology & Variables	Population & Sample Size	Results and Limitations
Headey, B. & Wooden, M. (2004). The effects of wealth and income on subjective well-being and ill-being	Regression Analysis (Ordinary Least Square)	2nd wave of the Household, Income and Labor Dynamics in Australia (HILDA) Survey conducted in 2002 N=7,934 prime working age individuals age 25-59.	A person who moved up the economic ladder from 25th income percentile to 75th income percentile would gain 2 percentiles on the life satisfaction scale and 8.7 percentiles on the financial satisfaction scale. Vice versa. A 2-percentile gain in life satisfaction would be 1.11 percentiles due to wealth and 0.9 due to income. Getting a job increases life satisfaction by 4.3 percentiles and increases financial satisfaction by 15.2 percentiles.
Helliwell, J. & Putnam, Ro. (2004). The social context of well-being.	Linear regression Life satisfaction on a 10-point scale, health status is on a five-point scale	World Values Survey/EVS (average about 1,000-1,500 in each country wave, 1980, 1991-1992, 1995-1997, 88,000 observations), the US Benchmark Survey (N=29,000), Social Sciences and Humanities Research Council of Canada (7,500)	Better self-reported health status increases life satisfaction by 0.65 point in life satisfaction (WVS), 0.54 point in happiness (WVS), 0.35 point in happiness (U.S. Benchmark) The authors recognize that the causal link between health and subjective well-being is not uncontroversial, although they tend to view well-being mainly as an effect, not a cause in this relationship.
Blanchflower, D. & Oswald, A. (2002). Well-being over time in Britain and the USA.	Regression analysis	N=1,500/year. Data from U.S. GSS from 1972 to 1998 N = 55,000 Britons. Data from Eurobarometer Surveys cross-section	Happiness and life satisfaction are U-shaped in age with a minim around age forty. Calculations suggest that to 'compensate' men for unemployment would take a rise in income at the mean of about $60,000 per year, and to 'compensate' for being black would take $30,000 extra per year. A lasting marriage is worth $100,000 per year compared to being widowed or separated.
Frey, B. S. & Stutzer, A.	Multiple regressions	Survey of >6,000	The following variables have the most consistent

Author, Publication Date, Title	Methodology & Variables	Population & Sample Size	Results and Limitations
(2002). Happiness and Economics: How the economy and institutions affect well-being	"How satisfied are you with your life as a whole these days?" 10-point scale	Switzerland residents by Leu, Burri, and Priester, collected 1992-1994.	and strongest correlation with SWB: Good health is an important factor in individual well-being. Age, gender, close relationship and marriage, education, nationality. Linear weighted least squares estimate: individuals with bad health are, on average, 0.74 points less satisfied with life than those with good health. Health has the second highest impact on life satisfaction, next to those who are separated compared to married persons (-0.948 points). Weighted order probit estimate: persons in bad health report a 13.3 percentage points lower probability of being completely satisfied than those in good health (ceteris paribus).
Clark, A. & Oswald, A. (2002). A simple statistical method for measuring how life events affect happiness	Regression Analysis Variables: income, labor market and life events – employment, marital status, health status	Data from the first seven waves of the British Household Panel Survey (BHPS)	The majority of well-being impact of unemployment stem from psychological impact rather than from the loss of wages. Getting married is calculated to bring each year the same amount of happiness, on average, as having an extra £70,000 ($110,000) of income per year. Widowhood brings a degree of unhappiness that would take, on average, an extra £170,000 ($267,000) per year to offset. In Great Britain, an unemployed man in a region with 20-25% unemployment would have the same level of well-being as an average employed man elsewhere.
Stack, S. & Eshleman, J. (1998) Marital Status and	Multiple regression analysis	World Values Study Group (1991) – data collected during 1981 to	Being married was 3.4 times more closely tied to the variance in happiness than was cohabitation, and marriage increases happiness equally among

Author, Publication Date, Title	Methodology & Variables	Population & Sample Size	Results and Limitations
Happiness: A 17-Nation Study		1983	men and women. The relationship between marital status and happiness holds in 16 of the 17 nations and the strength of the association does not vary significantly in 14 of the 17 nations.
NON-REGRESSION BASED STUDIES			
Dolan, P., Peasgood, T. & White, M. (2008). Do we really know what makes us happy? A review of the economic literature on the factors associated with subjective well-being	Meta analysis. Review of published research in economics journals since 1990.	19 major national and cross-national data sets that included measures of SWB.	Disability reduces life satisfaction on a 1-7 scale by 0.596 points for those with no past disability, by 0.521 points after 1 year of disability, 0.447 points after 2 years and 0.372 after 3 years. Unemployed have around 5 to 15% lower SWB scores than employed. Unemployment reduces the probability of a high life satisfaction score by 19% and a high overall happiness score by 15%.
Sirgy, J. (2012). The Psychology of Quality of Life: Hedonic Well-Being, Life Satisfaction, and Eudaimonia	Literature Review of Subjective Well-Being within Life Domains		Meta-analysis of 104 studies published before 1980 focusing on the American elderly concluded that objective and subjective measures of health account for 8-14% of the variance in subjective well-being (Okun, Stock, Haring, and Witter 1984) Perception of health status or health satisfaction plus domain satisfaction indicators explain 53% of the variation in respondents' reported happiness, 68% of the variance in life satisfaction scores, and 63% of the variance in reported satisfaction with overall QOL. (Michalos, Zumbo, and Hubley, 2000). 60% of the explained variance in happiness scores was attributable to health satisfaction (George & Landerman, 1984, Larsen, 1978, Michalos et al., 2007)

Appendix B: Simple Correlation Coefficients and Significance

	No Health Insurance Coverage	Cannot Afford Doctor	Medicaid Eligibility	Medicaid Scope	Medicaid Quality of Care	Medicaid Reimbursement	Medicaid Overall Score
No Health Insurance Coverage	1						
Cannot Afford Doctor	0.3602***	1					
Medicaid Eligibility	-0.0577***	-0.0418***	1				
Medicaid Scope	-0.0545***	-0.05***	0.6423***	1			
Medicaid Quality of Care	-0.0246***	-0.0114***	0.1327****	0.2121***	1		
Medicaid Reimbursement	-0.0077***	-0.018***	-0.1484***	-0.0637***	-0.1045***	1	
Medicaid Overall Score	-0.0644***	-0.0527***	0.7889***	0.7267***	0.489***	0.2782***	1
African American	0.0621***	0.0698***	-0.0592***	-0.1414***	-0.0453***	-0.0473***	-0.1149***
Asian	-0.006***	-0.0091***	0.0798***	0.0589***	-0.0084***	-0.0389***	0.0464***
Native Hawaiian	0.009***	0.0107***	0.0175***	0.0127***	-0.0042***	-0.0041***	0.0111***
American Indian	0.0471***	0.03***	-0.0431***	-0.0214***	-0.0312***	0.0494***	-0.0236***
Other Race	0.0032**	0.0068***	0.0133***	0.009***	0.009***	0.0212***	0.0236***
Multi Racial	0.0161***	0.0262***	0.0302***	0.0103***	-0.0193***	-0.0038**	0.0127***
Hispanic	0.1389***	0.0994***	-0.016***	0.0104***	-0.0475***	-0.0552***	-0.0488***
Female	-0.0189***	0.0523***	-0.0113***	-0.0187***	0.0072***	-0.008***	-0.0135***
Age	-0.2205***	-0.1652***	-0.0119***	-0.0139***	0.0127***	0.0026*	-0.0054***
Divorced	0.0568***	0.0762***	-0.0023	-0.0072***	-0.0002	-0.0021	-0.005***
Widowed	-0.082***	-0.0593***	-0.0218***	-0.0263***	0.0118***	-0.0054***	-0.019***
Separated	0.0537***	0.0696***	-0.0022	-0.0188***	0.0011	-0.0194***	-0.0146***
Never Married	0.1181***	0.0611***	0.0345***	0.0219***	0.0049***	-0.0267***	0.0185***
Unmarried Couple	0.0659***	0.0507***	0.0267***	0.0205***	-0.0013	-0.0094***	0.0181***
Number of children	0.1043***	0.0917***	-0.0055***	0.0111***	-0.0127***	0.0018	-0.0039***
Elementary	0.0674***	0.0577***	-0.0209***	-0.0229***	0.0004	-0.0127***	-0.0254***

	Health Insurance Coverage	Cannot Afford Doctor	Medicaid Eligibility	Medicaid Scope	Medicaid Quality of Care	Medicaid Reimbursement	Medicaid Overall Score
Some High School	0.0839***	0.074***	-0.0407***	-0.0559***	0.0005	-0.007***	-0.0443***
High School	0.0626***	0.0319***	-0.0344***	-0.0288***	0.0262***	0.0064***	-0.017***
Some College	0.0012	0.022***	-0.0098***	0.0096***	-0.0089***	0.0211***	0.0017
College Graduate	-0.131***	-0.1118***	0.0708***	0.0557***	-0.0174***	-0.0178***	0.0465***
Income <$10k	0.1187***	0.1257***	-0.0323***	-0.0438***	0.0034**	-0.0184***	-0.0388***
Income $10k to <$15k	0.0791***	0.0975***	-0.0267***	-0.033***	0.0106***	-0.0099***	-0.0261***
Income $15k to <$20k	0.1104***	0.0993***	-0.0299***	-0.0328***	0.0098***	-0.0053***	-0.0263***
Income $20k to <$25k	0.0843***	0.0708***	-0.0148***	-0.0083***	0.0088***	-0.0017	-0.0109***
Income $25k to <$35k	0.0281***	0.0197***	-0.0092***	-0.0031*	0.0009	0.0103***	-0.0021
Income $35k to <$50k	-0.0285***	-0.0274***	-0.0083***	0.0048***	-0.0044***	0.017***	0.0018
Income $50k to <$75k	-0.0826***	-0.0706***	0.0083***	0.0179***	-0.005***	0.0177***	0.0163***
Self Employed	0.0763***	0.0143***	0.0081***	0.0212***	-0.0085***	0.0196***	0.0164***
Unemployed more than 1 Year	0.1581***	0.128***	0.0139***	0.0022	0.0089***	-0.0224***	0.0033*
Unemployed less than 1 Year	0.1592***	0.0944***	0.0024	-0.0025	0.0019	-0.0118***	-0.0033*
Homemaker	0.0356***	0.0129***	-0.0318***	-0.0168***	-0.0111***	-0.0076***	-0.0325***
Student	0.0503***	0.0266***	0.0005	0.0029*	-0.0077***	-0.0057***	-0.0043***
Retired	-0.1672***	-0.1472***	-0.0102***	-0.0157***	0.0015	-0.0017	-0.0114***
Unable to Work	-0.0001	0.1198***	-0.0368***	-0.0529***	0.0203***	-0.0148***	-0.037***
Hours Worked Weekly	-0.0034	-0.0276***	0.098***	0.098***	0.098***	-0.098***	0.098***
Excellent Health	-0.0288***	-0.0842***	0.0369***	0.0341***	-0.0016	0.0001	0.0325***
Very Good Health	-0.0507***	-0.0895***	0.026***	0.0336***	-0.0034**	0.0128***	0.0294***
Good Health	0.0348***	0.0215***	-0.0143***	-0.0112***	-0.0008	0.0006	-0.0118***
Fair Health	0.0422***	0.1079***	-0.0296***	-0.0351***	0.0037**	-0.0126***	-0.0322***
Days of Poor Physical Health	0.0137***	0.1479***	-0.0282***	-0.037***	0.0128***	-0.0112***	-0.0279***
Days of Poor Mental Health	0.0895***	0.216***	-0.0113***	-0.023***	0.0126***	-0.0184***	-0.0161***

Days of not Enough Sleep	0.0557***	0.1844***	0.001	-0.005***	0.0167***	-0.0097***	0.0017
	African American	Asian	Native Hawaiian	American Indian	Other Race	Multi Racial	Hispanic
African American	1						
Asian	-0.0397***	1					
Native Hawaiian	-0.0142***	-0.0064***	1				
American Indian	-0.0349***	-0.0156***	-0.0056***	1			
Other Race	-0.0207***	-0.0093***	-0.0033*	-0.0082***	1		
Multi Racial	-0.0395***	-0.0177***	-0.0063***	-0.0156***	-0.0092***	1	
Hispanic	-0.0828***	-0.037***	-0.0133***	-0.0326***	-0.0194***	-0.0369***	1
Female	0.0437***	-0.0112***	-0.0035*	-0.0098***	-0.0125***	-0.0047***	0.0112***
Age	-0.0631***	-0.053***	-0.0301***	-0.0394***	-0.004***	-0.0275***	-0.1247***
Divorced	0.0384***	-0.0288***	-0.0023	0.0163***	0.003**	0.014***	-0.0146***
Widowed	-0.002	-0.0272***	-0.0101***	-0.0062***	-0.0015	-0.0065***	-0.0395***
Separated	0.0839***	-0.0078***	0.0001	0.0108***	-0.0006	0.0056***	0.0525***
Never Married	0.1407***	0.0174***	0.0131***	0.026***	0.0059***	0.0206***	0.0248***
Unmarried Couple	-0.0071***	-0.0084***	0.007***	0.0196***	0.0011	0.0127***	0.061***
Number of children	0.0305***	0.0284***	0.0281***	0.0422***	0.0048***	0.0105***	0.1261***
Elementary	0.0144***	-0.0116***	-0.0027*	0.0093***	0.0086***	-0.0036**	0.224***
Some High School	0.0706***	-0.0211***	0.0062***	0.0366***	0.0003	0.0122***	0.0737***
High School	0.0264***	-0.0376***	0.0056***	0.0083***	-0.0062***	-0.0023	-0.0079***
Some College	-0.0049***	-0.0229***	-0.001	0.0078***	0	0.0196***	-0.0372***
College Graduate	-0.062***	0.073***	-0.0065***	-0.0376***	0.0023	-0.0206***	-0.0844***
Income <$10k	0.0957***	-0.0087***	0.0059***	0.0467***	0.005***	0.0219***	0.0997***
Income $10k to <$15k	0.0405***	-0.016***	-0.001	0.0232***	0.0047***	0.0146***	0.0594***
Income $15k to <$20k	0.0533***	-0.0137***	0.0018	0.0202***	0.0037**	0.0103***	0.0555***
Income $20k to <$25k	0.0209***	-0.0164***	0.0005	0.0092***	0.0037**	0.0061***	0.0322***
Income $25k to <$35k	0.0151***	-0.0114***	0.0014	0.0013	0.0024	0.002	0.007***

	African American	Asian	Native Hawaiian	American Indian	Other Race	Multi Racial	Hispanic
Income $35k to <$50k	-0.015***	-0.0066***	0.002	-0.0055***	-0.0025	-0.0024	-0.0248***
Income $50k to <$75k	-0.0363***	0.002	-0.0017	-0.0159***	-0.0061***	-0.0088***	-0.0486***
Self Employed	-0.044***	-0.001	-0.0048***	-0.0065***	0.0019	-0.0015	-0.017***
Unemployed more than 1 Year	0.0425***	0.0033**	0.0114***	0.0193***	0.0039***	0.0116***	0.0235***
Unemployed less than 1 Year	0.0324***	0.0005	0.0064***	0.02***	-0.001	0.0106***	0.0265***
Homemaker	-0.0481***	0.0019	0.0003	-0.0058***	-0.0029*	-0.0067***	0.0768***
Student	0.0245***	0.0273***	0.0069***	0.0156***	0.0056***	0.0176***	0.028***
Retired	-0.0321***	-0.0282***	-0.0153***	-0.0286***	-0.0036**	-0.0162***	-0.0816***
Unable to Work	0.0782***	-0.027***	-0.0026	0.0354***	0.0065***	0.0339***	0.0209***
Hours Worked Weekly	-0.0348***	-0.0251***	-0.0039	-0.0001	-0.0024	-0.0042	-0.0163
Excellent Health	-0.0407***	0.014***	-0.0007	-0.0145***	0.0007	-0.0123***	-0.0248***
Very Good Health	-0.053***	-0.0061***	-0.0064***	-0.0246***	-0.0065**	-0.0156***	-0.0684***
Good Health	0.0325***	0.0158***	0.0055***	0.0106***	0.0021	0.0016	0.0223***
Fair Health	0.0568***	-0.0156***	0.0022	0.0175***	0.003**	0.0166***	0.0739***
Days of Poor Physical Health	0.0198***	-0.0305***	-0.0034**	0.0239***	0.0031**	0.0295***	0.0155***
Days of Poor Mental Health	0.024***	-0.0262***	0.0004	0.0256***	0.0059***	0.0298***	0.0211***
Days of not Enough Sleep	0.0209***	-0.0218***	0.0025	0.0168***	0.0079***	0.0311***	0.0037**
	Female	Age	Divorced	Widowed	Separated	Never Married	Unmarried Couple
Female	1						
Age	0.0348***	1					
Divorced	0.0345***	0.028***	1				
Widowed	0.1752***	0.4444***	-0.1685***	1			
Separated	0.0225***	-0.0553***	-0.0586***	-0.0605***	1		
Never Married	-0.0481***	-0.2917***	-0.145***	-0.1498***	-0.0521***	1	
Unmarried Couple	-0.0081***	-0.1171***	-0.0587***	-0.0606***	-0.0211***	-0.0522***	1

	Female	Age	Divorced	Widowed	Separated	Never Married	Unmarried Couple
Number of children	0.0118***	-0.5062***	-0.0723***	-0.179***	0.0447***	-0.0267***	0.0385***
Elementary	-0.0017	0.0775***	-0.0093***	0.0768***	0.0318***	-0.0221***	0.0145***
Some High School	0.0083***	0.023***	0.0101***	0.0709***	0.0417***	0.0205***	0.0134***
High School	0.0181***	0.0679***	0.002	0.0774***	0.009***	0.0004	-0.0124***
Some College	0.0393***	-0.0328***	0.0325***	-0.0148***	-0.003**	0.0016	-0.0013
College Graduate	-0.0578***	-0.0768***	-0.0336***	-0.1268***	-0.0399***	-0.0038*	0.0005
Income <$10k	0.0537***	-0.0047***	0.1037***	0.0428***	0.0837***	0.1037***	0.0091***
Income $10k to <$15k	0.0467***	0.0841***	0.0855***	0.1354***	0.0421***	0.0379***	0.0031*
Income $15k to <$20k	0.042***	0.0765***	0.0503***	0.1237***	0.0323***	0.034***	0.0073***
Income $20k to <$25k	0.0294***	0.0788***	0.0379***	0.0959***	0.0123***	0.0215***	0.0077***
Income $25k to <$35k	0.0157***	0.0764***	0.0269***	0.0573***	-0.0034**	0.0164***	-0.0042***
Income $35k to <$50k	-0.0093***	0.0214***	0.0013	-0.0241***	-0.0176***	-0.0025	-0.0032*
Income $50k to <$75k	-0.0214***	-0.0601***	-0.0372***	-0.0911***	-0.0283***	-0.0233***	-0.0066***
Self Employed	-0.1063***	-0.0576***	-0.0072***	-0.0782***	-0.0053***	-0.0178***	0.011***
Unemployed more than 1 Year	-0.011***	-0.0767***	0.0324***	-0.0382***	0.0274***	0.0697***	0.019***
Unemployed less than 1 Year	-0.026***	-0.1137***	0.0226***	-0.0489***	0.0224***	0.0682***	0.029***
Homemaker	0.2154***	-0.0133***	-0.0904***	0.0226***	-0.0124***	-0.0792***	-0.0045***
Student	0.0023	-0.2233***	-0.0256***	-0.0478***	0	0.2015***	0.0276***
Retired	-0.0173***	0.6244***	-0.0272***	0.3217***	-0.0547***	-0.1301***	-0.064***
Unable to Work	0.0225***	0.0011	0.1047***	0.0106***	0.0762***	0.0411***	-0.002
Hours Worked Weekly	-0.3272***	-0.1289***	-0.0045	-0.1414***	-0.0112	0.0036	-0.0085
Excellent Health	-0.0019	-0.1327***	-0.0282***	-0.0773***	-0.0211***	0.0063***	0.0049***
Very Good Health	-0.0023	-0.0748***	-0.0357***	-0.0527***	-0.0293***	-0.0075***	0.0001
Good Health	-0.0102***	0.0441***	-0.001	0.0254***	-0.0005	0.0121***	0.0016
Fair Health	0.0149***	0.1163***	0.0362***	0.0754***	0.0338***	-0.0024	-0.0002
Days of Poor Physical Health	0.035***	0.1229***	0.0756***	0.0745***	0.0441***	-0.0144***	-0.0065***

Days of Poor Mental Health	0.0644***	-0.0902***	0.0851***	-0.0167***	0.0743***	0.0427***	0.0231***
Days of not Enough Sleep	0.0507***	-0.2026***	0.0521***	-0.0805***	0.0521***	0.0336***	0.0265***
	Number of Children	Elementary	Some High School	High School	Some College	College Graduate	Income <$10k
Number of Children	1						
Elementary	0.0064***	1					
Some High School	0.0093***	-0.0474***	1				
High School	-0.0571***	-0.1201***	-0.1684***	1			
Some College	-0.0008	-0.1105***	-0.155***	-0.393***	1		
College Graduate	0.0486***	-0.1316***	-0.1846***	-0.4678***	-0.4306***	1	
Income <$10k	-0.0166***	0.1481***	0.1418***	0.0423***	-0.0341***	-0.1326***	1
Income $10k to <$15k	-0.0429***	0.1014***	0.1083***	0.0688***	-0.0169***	-0.1394***	-0.0649***
Income $15k to <$20k	-0.0283***	0.0683***	0.094***	0.0947***	-0.0111***	-0.1505***	-0.0739***
Income $20k to <$25k	-0.0361***	0.0219***	0.0488***	0.0949***	0.0136***	-0.1349***	-0.0828***
Income $25k to <$35k	-0.0425***	-0.0032**	0.0038**	0.0803***	0.0333***	-0.108***	-0.0919***
Income $35k to <$50k	-0.0267***	-0.048***	-0.0463***	0.0269***	0.0505***	-0.0323***	-0.1047***
Income $50k to <$75k	0.0157***	-0.0649***	-0.0756***	-0.0568***	0.0323***	0.0848***	-0.1067***
Self Employed	0.0328***	-0.0262***	-0.0305***	-0.0341***	-0.0013	0.06***	-0.0343***
Unemployed more than 1 Year	0.0165***	0.0058***	0.0323***	0.0199***	0.0083***	-0.0457***	0.1223***
Unemployed less than 1 Year	0.0436***	-0.0032**	0.0167***	0.0205***	0.0106***	-0.0371***	0.0546***
Homemaker	0.1296***	0.0616***	0.0406***	0.0368***	-0.0173***	-0.0642***	0.0219***
Student	0.0588***	-0.0197***	0.0129***	-0.0155***	0.0545***	-0.0347***	0.0332***
Retired	-0.3034***	0.0231***	0.0135***	0.0539***	-0.016***	-0.0526***	-0.0272***
Unable to Work	-0.0536***	0.0953***	0.1227***	0.0417***	-0.0066***	-0.1339***	0.234***
Hours Worked Weekly	0.0494***	-0.0281***	-0.0393***	-0.0073	-0.0266***	0.0521***	-0.0885***
Excellent Health	0.0865***	-0.0537***	-0.0664***	-0.0958***	-0.0236***	0.1692***	-0.0662***
Very Good Health	0.0344***	-0.0833***	-0.0833***	-0.0596***	0.021***	0.1129***	-0.0962***
Good Health	-0.0214***	-0.0037**	0.0156***	0.0691***	0.0165***	-0.0886***	-0.0071***

Fair Health	-0.0639***	0.0993***	0.0954***	0.0675***	-0.012***	-0.141***	0.1075***
Days of Poor Physical Health	-0.0852***	0.0825***	0.0915***	0.0515***	0.0066***	-0.1329***	0.1589***
Days of Poor Mental Health	0.0237***	0.0363***	0.0712***	0.0276***	0.0206***	-0.0958***	0.1424***
Days of not Enough Sleep	0.1347***	0.0018	0.0298***	-0.0059***	0.0267***	-0.0351***	0.0647***
	Income $10k to <$15k	Income $15k to <$20k	Income $20k to <$25k	Income $25k to <$35k	Income $35k to <$50k	Income $50k to <$75k	Self Employed
Income $10k to <$15k	1						
Income $15k to <$20k	-0.0782***	1					
Income $20k to <$25k	-0.0875***	-0.0997***	1				
Income $25k to <$35k	-0.0972***	-0.1108***	-0.124***	1			
Income $35k to <$50k	-0.1107***	-0.1261***	-0.1412***	-0.1569***	1		
Income $50k to <$75k	-0.1128***	-0.1285***	-0.1439***	-0.1598***	-0.182***	1	
Self Employed	-0.0386***	-0.0285***	-0.024***	-0.0198***	0.0002	0.0085***	1
Unemployed more than 1 Year	0.0504***	0.0415***	0.0286***	-0.0051***	-0.0278***	-0.0423***	-0.0551***
Unemployed less than 1 Year	0.0246***	0.0364***	0.0281***	0.0018	-0.0103***	-0.0214***	-0.0508***
Homemaker	0.0042***	0.009***	0.0078***	-0.0021	-0.0069***	-0.0175***	-0.0862***
Student	0.0082***	0.0085***	0.007***	-0.0025	-0.0085***	-0.0093***	-0.0382***
Retired	0.0556***	0.067***	0.0841***	0.0843***	0.042***	-0.0414***	-0.1942***
Unable to Work	0.1698***	0.0841***	0.0276***	-0.0271***	-0.066***	-0.0854***	-0.0832***
Hours Worked Weekly	-0.0946***	-0.0943***	-0.0638***	-0.0332***	0.0038	0.0376***	0.1386***
Excellent Health	-0.0733***	-0.0705***	-0.0613***	-0.0489***	-0.0167***	0.0303***	0.0739***
Very Good Health	-0.0883***	-0.0776***	-0.0472***	-0.0191***	0.0245***	0.0659***	0.0309***
Good Health	0.0057***	0.0282***	0.0346***	0.0453***	0.0305***	-0.0041**	-0.0242***
Fair Health	0.105***	0.0946***	0.0612***	0.025***	-0.0252***	-0.0694***	-0.0513***
Days of Poor Physical Health	0.1385***	0.0899***	0.0538***	0.0072***	-0.0402***	-0.0757***	-0.0679***
Days of Poor Mental Health	0.0895***	0.0619***	0.0334***	-0.0043***	-0.0304***	-0.05***	-0.0365***
Days of not Enough Sleep	0.0349***	0.0177***	-0.002	-0.0224***	-0.0209***	-0.0092***	-0.0171***

	Unemployed more than 1 Year	Unemployed less than 1 Year	Homemaker	Student	Retired	Unable to Work	Hours Worked Weekly
Unemployed more than 1 Year	1						
Unemployed less than 1 Year	-0.0311***	1					
Homemaker	-0.0527***	-0.0486***	1				
Student	-0.0233***	-0.0215***	-0.0365***	1			
Retired	-0.1187***	-0.1095***	-0.1856***	-0.0822***	1		
Unable to Work	-0.0509***	-0.0469***	-0.0796***	-0.0352***	-0.1793***	1	
Hours Worked Weekly	.	.	.	.	.	.	1
Excellent Health	-0.0252***	-0.0096***	0.008***	0.0253***	-0.0906***	-0.1109***	0.0211**
Very Good Health	-0.0312***	-0.0049***	-0.0106***	0.012***	-0.0416***	-0.1504***	0.017*
Good Health	0.0185***	0.0158***	0.0027*	-0.0038*	0.0462***	-0.0632***	0.0016
Fair Health	0.0317***	0.0053***	0.0143***	-0.0211***	0.0743***	0.1626***	-0.0476***
Days of Poor Physical Health	0.0325***	-0.0048***	-0.0112***	-0.0274***	0.0505***	0.3834***	-0.0744***
Days of Poor Mental Health	0.0779***	0.052***	-0.0081***	0.0153***	-0.101***	0.2722***	-0.0258***
Days of not Enough Sleep	0.0323***	0.0127***	-0.0056***	0.0236***	-0.1832***	0.1649***	0.076***

	Excellent Health	Very Good Health	Good Health	Fair Health	Days of Poor Physical Health	Days of Poor Mental Health	Days of not Enough Sleep
Excellent Health	1						
Very Good Health	-0.3133***	1					
Good Health	-0.3061***	-0.4536***	1				
Fair Health	-0.1851***	-0.2743***	-0.2681***	1			
Days of Poor Physical Health	-0.187***	-0.2257***	-0.0913***	0.2737***	1		
Days of Poor Mental Health	-0.1185***	-0.1207***	-0.0208***	0.1459***	0.347***	1	
Days of not Enough Sleep	-0.0909***	-0.0772***	-0.0109***	0.103***	0.2442***	0.332***	1

Note: * denotes 10% significance, ** denotes 5% significance, * denotes 1% significance

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