Health Inequality and Its Determinants in New York[1]

by

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Summary: Self-assessed health status conditioned by several objective measures of health and socio-demographic characteristics are used to measure health inequality. We compare the quality of health and health inequality among different racial/ethnic groups as well as across 17 regions in New York State. In terms of average health and health inequality, American Indian/Alaskan Natives and Hispanics are found to be the worst, and North Country, Bronx County, and Richmond County lag behind the rest of the State. Three major contributing factors to health inequality are found to be employment status, education, and income. However, the contribution of each of these determinants varies significantly among racial/ethnic groups as well as across regions, suggesting targeted public health initiatives for vulnerable populations to eliminate overall health disparity.

Keywords: BRFSS data; Self-assessed health; Ordered Probit; Health inequality; Gini coefficient; Lorenz curve; Decomposition analysis

1. Introduction

The goals of Healthy People 2010 - the national statement on health objectives in the U.S. - are twofold: first, to help individuals of all ages to increase life expectancy and to improve their quality of life; and second, to eliminate health disparities among segments of the population, including differences that occur by gender, race or ethnicity, education or income, disability, geographic location, and sexual orientation (US-DHHS, 2000).

Achieving the Healthy People 2010 goals needs effective public policies that require a precise and consistent measure of quality of health and health inequality.[2] Different groups of the population have different quality of health and socioeconomic characteristics, which vary considerably over regions. In addition, the causes of within group health inequality may also be different for different groups. A large number of studies have reported that socioeconomic status (SES) is a key factor affecting quality of health and health inequality (see for example, Adler and Newman, 2002; Cutler and Lleras-Muney, 2006; Adams *et al*., 2003; Cutler *et al*., 2006; Deaton, 2006). There are four broad pathways—health care, environmental exposure, health behavior, and chronic stress—through which SES affects health (Adler and Ostrove, 1999). Because SES is an important mediator of quality of health, studying health disparity cannot be separated from studying disparity in SES. In order to improve quality of health and to eliminate health disparity, policy makers need to identify the main sources of disparity within different groups, especially those related to SES, so they can prioritize what policy that best suited for particular group. For example, the quality of health of a particular group

[2] We will use "inequality" and "disparity" interchangeably in this paper to mean differences in health status within and between groups of people.

may be improved more effectively through education, for another group better health insurance or employment initiatives may be more effective.

Numerous studies on measuring quality of health and health disparity have focused on mortality rates, prevalence of diseases/risk factors, psychological morbidity, quality of or access to health care services, and health care utilization rates.[3] In this study we focus on a measure of health more generally, and calculate a health index and health inequality based on self-assessed health (SAH) status. SAH is defined as the response to the survey question "Would you say that in general your health is: excellent, very good, good, fair, or poor?" (*Centers for Disease Control and Prevention* [CDC], 1999-2004a).

SAH has been shown to be a good measure of overall health conditions. In their review, Idler and Benyamini (1997) show that SAH has strong predictive validity of mortality. Sickles and Taubman (1997) compiled results from worldwide studies on the association between self-assessed health and mortality, and reported that lower level of SAH is associated with higher mortality odds. Manor *et al*. (2001) found that SAH has a strong association with longstanding illness. Furthermore, Lahiri *et al*. (1995) show that SAH is a useful predictor of the severity of diseases and disability. Humphries and van Doorslaer (2000) found that health inequality calculated on the basis of SAH status gives similar results to those calculated based on a more objective health indicator (*viz.* McMaster Health Utility Index). More recently, Safaei (2006) found SAH to be statistically more reliable than the binary chronic conditions as a measure of overall health.

[3] See, for instance, Williams and Collins (1995), Ayanian *et al*. (1999), Shishehbor *et al*. (2006), and Safaei (2006).

In this paper SAH is modeled using an Ordered Probit model (McKelvey and Zavoina, 1975). The predicted value from this model, which is conditioned by several objective determinants including different diseases or risk factors, and socio-demographic characteristics, is used as a measure of individual health. This predicted value is utilized to measure health inequality using Gini coefficient and Lorenz curve (Kakwani *et al*. 1997). Furthermore, to be useful for policy purposes, health inequality is decomposed into its determinants (Wagstaff *et al.* 2003).

The primary goal of this paper is to measure health inequality between and within racial/ethnic groups as well as across the regions of New York State. Furthermore, the within-group health inequalities are decomposed into their determinants that characterize the sources of inequality for different groups. This is the first study to look at the health status of New Yorkers along these dimensions.

The paper is organized as follows. Section 2 describes the estimation procedures of SAH - the methods to calculate quality of health, health inequality and the contributions of its determinants. The data used in the empirical analysis are described in Section 3. The results are presented in section 4. Finally, section 5 summarizes our conclusions.

2. Methods

We follow the same procedures as Cutler and Richardson (1997, 1998) and Groot (2000) in empirical modeling of the quality of health. In this case, three related concepts are distinguished: a true quality of health denoted as h^*, a vector of objective measures of health denoted as $\mathbf{h}^o$, and a subjective measure of health denoted as h^s. The true quality of health is a latent variable, which is unobservable. What we observe is a vector of objective measures and a subjective measure of health. The true unobserved quality of health h^* is assumed to be a function of the vector of objective measures of health, and a vector of individual characteristics denoted by **x**. The subjective health is measured on an ordinal scale with *m*-category self-assessed response. For the purpose of measuring quality of health and health inequality we transform this ordinal scale variable into a cardinal variable using an ordered response model. To control for possible heterogeneity in self-assessed health, we estimate an Ordered Probit model with heteroskedasticity in errors. The model is formulated as follows:

$$h_i^* = \mathbf{h}_i^o \boldsymbol{\gamma} + \mathbf{x}_i \boldsymbol{\beta} + s(\mathbf{z}_i, \eta)\varepsilon_i \qquad (1)$$

$$h_i^s = j \Leftrightarrow \mu_{\mathrm{j}} \le h_j^* \le \mu_{j+1} \text{ for } j = 0,1,..,m-1$$

$$\mu_0 = -\infty \text{ and } \mu_m = +\infty$$

$$i = 1, 2, ..., n$$

where $\boldsymbol{\gamma}$, $\boldsymbol{\beta}$, $\boldsymbol{\eta}$ are vectors of coefficients, $\boldsymbol{\mu} = (\mu_1, \ldots, \mu_{m\text{-}1})$ is an unknown vector of thresholds to be estimated together with the vectors of coefficients, ε_i is the error term assumed to be normally distributed, $s(\mathbf{z}_i, \boldsymbol{\eta}) = \sigma\sqrt{(1 + \exp(\mathbf{z}_i \boldsymbol{\eta}))}$ is a scale function to control for heteroskedasticity, and n is the number of observations. $\mathbf{z}_i$ is a vector of observed variables that affect the variance of the error term.[4]

The model is estimated using maximum likelihood estimation. The predicted quality of health, $\hat{h}_i^* = \mathbf{h}_i^o \hat{\boldsymbol{\gamma}} + \mathbf{x}_i \hat{\boldsymbol{\beta}}$, is used as a measure of individual health. The predicted health from the estimated Ordered Probit model will purge at least some part of the variation in SAH that is due to subjective idiosyncrasies of the respondents, not supported

[4]van Doorslaer and Jones (2003) have shown that this heteroskedastic model accommodates possible individual-specific heterogeneity in the subjective thresholds $\boldsymbol{\mu}$.

by objective health measures. Following van Doorslaer and Jones (2003), we re-scale this prediction to be in the [0, 1] interval as $h_i = (\hat{h}_i^* - \hat{h}_{\min}^*)/(\hat{h}_{\max}^* - \hat{h}_{\min}^*)$, where $\hat{h}_{\max}^*$ and $\hat{h}_{\min}^*$ are the maximum and the minimum of the predicted quality of health, respectively.

Using the estimated quality of health h_i, we measure health inequality using pseudo-Lorenz curves and health Gini coefficients (Wagstaff *et al*., 1991).[5] A pseudo-Lorenz curve plots the cumulative proportion of health $L(s)$ against the cumulative proportion of population s (starting with the lowest health and ending with the highest health), as shown in Figure 1. If the Lorenz curve $L(s)$ coincides with the diagonal, health is equally distributed. This means that there is no health inequality in the population. The farther the Lorenz curve is from the diagonal, the bigger is the degree of inequality. The area between Lorenz curve and the diagonal provides a measure of inequality. The Gini coefficient is defined as twice the area between the Lorenz curve and the diagonal. The coefficient ranges from 0 (when everybody enjoys exactly the same health) to 1 (when all population's health is concentrated in the hands of one person).

Gini coefficient can be calculated using equation (see Kakwani *et al*., 1997):

$$\hat{G} = \frac{2}{n\mu}\sum_{i=1}^{n} h_i R_i - 1 \tag{2}$$

where R_i is the i^{th} individual fraction rank in health and μ is the mean of quality of health. The variance is estimated using the Huber-White procedure. The disadvantage of the Gini coefficient is its lack of straightforward interpretation in a natural unit, while its advantage is that it takes into account both coefficient variation of health and correlation between health and health rank (Milanovic, 1997).

[5] See also Lecluyse and Cleemput (2005) and Clarke and Ryan (2006).

Furthermore, to be more meaningful for policy purposes, health inequality is decomposed into its determinants as demonstrated by Wagstaff *et al*. (2003). Define a vector of explanatory variables as $\mathbf{w} = (\mathbf{h}^{o}\ \ \mathbf{x})$**.** Given the relationship between health and explanatory variables as in equation (1), the Gini coefficient can be written as

$$\hat{G} = \sum_{k=1}^{K} \left(\hat{\beta}_k \overline{w}_k / \overline{h} \right) G_k \tag{3}$$

where $\overline{h}$ is the mean of h, $\overline{w}_k$ is the mean of variable w_k from the vector of explanatory variables **w,** and G_k is Gini coefficient ranked by health for variable w_k.

3. Data, descriptive statistics, and imputation

3.1. Data

The data used in this study are obtained from the New York State sample of the *Behavioral Risk Factor Surveillance System* (BRFSS) over 1999-2004, with 22,083 sample observations (*Centers for Disease Control and Prevention* [CDC], 1999-2004b).[6] Every year health departments of all states, with technical and methodological assistance from the Centers for Disease Control and Prevention (CDC), conduct monthly telephone interviews on randomly selected non-institutional adults aged 18 years or older. The surveys are developed and conducted to monitor major behavioral risks among adults associated with premature morbidity and mortality. The number of observations is not the same for all variables. The differences can be attributed to: (i) the absence of some questions in certain years—for example, coronary heart disease was asked only in the interviews for the years of 1999, 2001, and 2003; and (ii) missing values due to “do not know”, “not sure” responses, and refusals to answer.

[6] Sehili *et al.* (2005) have used this data source to study health inequality in the U.S. in terms of physically healthy days.

Table 1 presents the pattern of the missing values attributed to the absence of questions in the survey questionnaires. In order to include all important diseases and risk factors as covariates in equation (1), we needed to fill in the missing values in our pooled sample. Otherwise, an omitted variable bias would result in the coefficient estimates of included variables. A currently accepted procedure to impute missing values is the multiple-imputation method of Rubin (1987) and Schafer (1997).[7] More detail on the multiple imputation method is presented in the Appendix.

In this paper, racial/ethnic groups included in the comparisons are non-Hispanic White (White), non-Hispanic Black (Black), Hispanic, Asian/Pacific Islander (Asian), and American Indian Alaskan Native (AIAN). We divide New York State into 17 regions, which consist of 9 counties of Downstate and 8 economic development regions of Upstate (see Table A2 in the appendix). Upstate New York is divided into broader economic development regions due to small samples in some individual counties. Descriptive statistics of all variables by racial/ethnic groups are presented in Table A3, while the descriptive statistics by regions are presented in Table A4. For some variables, the descriptive statistics for Asian and AIAN groups are not reported because of sample size. In this case, we follow the BRFSS guideline that the minimum number of observations for meaningful for interpretation between groups is 50. As reported in Table A3 and Table A4, the descriptive statistics of most of variables vary between racial/ethnic groups as well as across the regions.

[7] In this study, we use SAS® to perform the multiple-imputation procedure and also all other calculations.

4. Results

4.1. Coefficient estimates

Table 2 presents the coefficient estimates of equation (1).[8] Since this study is based on pooled cross-section observational data without controlling for endogeneity, the coefficient estimates do not necessarily suggest any causality relationship - they merely reflect a measure of association between quality of health and the explanatory variables. So it is possible that the association reflects reverse causality. For example, good health may have a positive effect on income. However, the higher is the absolute value of the coefficient, stronger is the association between the quality of health and the corresponding explanatory variable.

As the SAH ranges from “poor“ (=1) to “excellent“ (=5), a positive (negative) coefficient of an explanatory variable indicates that a higher value of the variable is associated with a higher (lower) quality of health. From Table 2, we can see that health status declines steadily as age increases from age group of 25–39 years. The negative coefficient estimate for gender indicates that females are healthier than males on average. All racial/ethnic dummies have negative coefficient estimates, implying that even after controlling for objective health measures, the self-assessed health status of the minority populations are lower than that of White population. It may mean that there are omitted covariates in the regression (*e.g.,* severity of diseases and risk factors, neighborhood effects, discrimination, etc.) that systematically affect the health of the minorities. Kobetz

[8] We also estimated the model using interval regression with thresholds as reported in van Doorslaer and Jones (2003); however based on a number of alternative measures of goodness of fit, which is the association between actual SAH and predicted SAH (*e.g.*, gamma coefficient, Spearman correlation, and Kenadall’s Tau-b), ordered probit model gave significantly higher goodness of fit. Therefore we estimated the model using ordered probit model.

et al. (2003) found that neighborhood poverty is associated with a greater likelihood of poor SAH.[9]

The negative coefficient estimate of body mass index indicates that a higher body mass index is associated with a lower quality of health. With elementary school or lower education as the reference, the coefficient estimate of each dummy for education level is positive and increases as education level increases. These estimates tell us that a higher education level is associated with a better quality of health. The negative coefficient estimate of the dummy for living in New York City indicates that the conditional mean of the quality of health of New York City population is lower than that of the rest of the New York State population. It is noteworthy that the dummies for other cities such as Utica, Syracuse, Buffalo, Rochester, and Albany were not statistically significant and therefore were excluded from the equation. Respondents having a health plan have better quality of health than those without a health plan, as expected. The coefficient estimate of annual household income is positive indicating that higher income is associated with a better quality of health.

The coefficient estimate of smoking status is negative which indicates smokers have lower quality of health than non-smokers. Participating in physical activities or exercise has a positive association with the quality of health. Consuming more fruits and vegetables is associated with a better quality of health. This finding is consistent with the belief that dietary differences in fruits and vegetables contribute to differences in morbidity for chronic diseases (James and Nelson, 1997). A number of researchers have found that poor neighborhoods tend to have poor diets; certain aspects of disadvantaged

[9] It may also be due to relatively different thresholds used by White while reporting SAH, see Banks *et al.* (2006). However, this explanation is less likely in our case because we allow for heteroskedastic errors where the race/ethnicity variables are statistically significant. See fn. 4.

neighborhoods act to hinder the procurement of healthy food, see Ecob and MacIntyre (2000) and Diez-Roux *et al.* (1999). Thus, the fruit & vegetable variable in our regression may be capturing certain omitted neighborhood characteristics too that affect health adversely.

All coefficient estimates of health variables (diseases and risk factors) are negative as expected, and almost all of them are statistically significant at 5% level. The relative magnitudes of the coefficient estimates are quite sensible. Diseases or risk factors generally considered serious such as diabetes, coronary heart disease, myocardial infarction, and stroke have relatively high coefficient estimates in absolute value. While diseases or risk factors considered less serious have relatively low coefficient estimates in absolute value. These findings based on the New York State population are broadly consistent to the results obtained by Cutler and Richardson (1997, 1998) and Groot (2000) based on the U.S. population.

In many studies, it has been debated whether higher income inequality in a society is associated with poor average quality of health. Van Ourti *et al*. (2006) show that when the relationship between income and health is concave, proportional income growth increases average quality of health, and rising income inequality reduces average quality of health. Wilkinson and Pickett (2006) compile results from 155 published peer review papers on the subject of the relationship between income inequality and population health. Around seventy percent of the results suggest that health status is lower in societies where income is more unequal. The proponents of the association between income inequality and health are, for example, Wilkinson (1992), Kennedy *et al*. (1998), Soobader and LeClere (1999), and Subramanian and Kawachi (2004, 2006). Studies on the relationship between income inequality and health have been conducted using various levels of data, from census track level to national level, and based on cross section and time series data.

Deaton and Lubotsky (2003) have, however, found that after controlling for the racial composition of population in a city, the effect of income inequality on health disappears. They argue that the higher the percentage of minorities (e.g., Blacks) the higher is the income inequality in the city. In addition to the specification reported in Table 2, we also estimated equation (1) with three additional variables: county Gini coefficient (as a measure of income inequality), percent blacks, and percent Hispanics. We found that the coefficients of all these variables were insignificant when the dummy for New York City was included. Without the New York City dummy, however, the Gini coefficient was significant in this multilevel regression even when we controlled for percent blacks and percent Hispanics. In our case, it can be explained by the fact that the patterns of income inequality and percent blacks across regions are quite different and, hence, are not collinear as presented in Figures 2 and 3. Since the New York City dummy is picking up the effect of the three additional variables above and the effect of income inequality is weak, we decided to use the specification presented in Table 2 in subsequent analysis.

Table 3 presents the coefficient estimates of the scale function. These coefficient estimates indicate that the error in equation (1) is heteroskedastic and is a function of gender, age, race/ethnicity, annual household income, having health plan, and education. We should, however, note that reporting heterogeneity in health status does not have a large quantitative impact on measures of health inequality, see d'Uva *et al*. (2006).

4.2. Quality of health

4.2.1. Quality of health by race/ethnicity

Table 4 presents the average quality of health and health adjusted life expectancy (HALE). Among racial/ethnic groups, Asian followed by White has the highest average quality of health, while AIAN followed by Hispanic and Black has the lowest. The average age varies considerably among racial/ethnic groups from 38.6 years through 47.6 years (see Table A3 in appendix). In addition, the average quality of health of a group depends on age distribution in the group. A group with a higher proportion of young individuals, *ceteris paribus*, will have a better quality of health relative to groups with a lower proportion of young individuals. Comparing quality of health between groups in a population with different age distributions could be misleading.

Several methods can be used to control for the effects of age distribution. The simplest method is by comparing the average estimated quality of health between groups of the population by ages. Another method is by incorporating the quality of health into the life table of the group. In other words, we combine morbidity and mortality data to obtain the estimates of Health Adjusted Life Expectancy (HALE) (see Molla *et al*., 2003). The HALE measures the expected life (years) in perfect health condition. This measure is also called Healthy Life Expectancy (HLE). Since dependable life tables for different racial/ethnic groups are not available, in this study HALE is calculated based on the general U.S. population life table of 2002 (Arias, 2004). Thus HALE estimated in this paper is used to compare the quality of health between groups of the population that eliminates the effect of age distribution without differentiating the mortality rates among the groups. HALE for each racial/ethnic group by ages are presented in Table 4.

The table shows that White in the youngest age group (20-24) has the highest HALE followed by Asian, and Hispanic has the lowest followed by AIAN. A 20-year old White individual is expected to live for 44.2 years in perfect health condition, while a Hispanic individual with the same age is expected to live for 36.8 years in perfect health condition. Thus, at age 20, a White individual is expected to live almost 7.5 years in perfect health longer than a Hispanic individual. It is clear from these results that by eliminating the effect of age distribution White does better than Asian, while Hispanic does worse than AIAN. This is a remarkable result. Also note that if HALE for each racial/ethnic group were calculated based on their own life tables, the disparity across racial/ethnic groups could be higher since quality of health is correlated with life expectancy (Mullahy, 2001).

4.2.2. Geography of health

In this part, we do not compute HALE for each region for two reasons. First, the distributions of age across the regions are very similar so the effect of age distribution is negligible. Second, not all regions have enough observations required to compute HALE. The average quality of health by regions is presented in Figure 4. Nassau, Suffolk, Rockland, and Westchester Counties are in the brightest areas reflecting the highest quality of health. In contrast, Bronx County is in the darkest area followed by Richmond County, North Country, Kings County, Queens County, and Southern Tier. None of the Upstate regions is in the brightest areas, while Downstate regions vary from the brightest to the darkest, indicating that health disparity across Downstate regions is higher than that across Upstate regions.

It is very common that quality of health is measured using dichotomized SAH, *cf.* CDC. For example, quality of health of a group may be defined as a percentage of individuals in “very good“ and “excellent“ health status (*e.g.,* Keppel *et al*. 2004); or it may be defined as the complement of the percentage of individuals in “poor“ and “fair“ health status. Unfortunately, this means that the health rank of a group depends on the chosen cut-off point in dichotomizing the SAH status. Figures A1 and A2 in the Appendix present the patterns of quality of health using the two different cut-off points. From both figures, it is obvious that the two different cut-off points give two somewhat different patterns of quality of health. The procedure used in this paper circumvents this problem of arbitrariness.

4.3. Health inequality

Similar to quality of health, we also compare health inequality between racial/ethnic groups as well as across regions. In addition, this section also presents decomposition results for each racial/ethnic group and for different regions.

4.3.1. Health inequality by race/ethnicity

Gini coefficients by race/ethnicity with corresponding 95%-confidence intervals are presented graphically in Figure 5. All coefficients are significantly greater than zero, indicating that health inequality exists in all groups. There is, however, substantial variation in the coefficients among groups. The highest health inequality is found within AIAN group followed by Hispanic. The lowest health inequality is found within Asian group followed by White. The figure also shows that the differences in Gini coefficients between groups are statistically significant.

Another way to compare health inequality between groups is by comparing their Lorenz curves. Figure 6 presents the Lorenz curves expressed as the deviation of the Lorenz curve from the diagonal in order to amplify the differences between racial/ethnic groups. The figure provides more obvious evidence of the differences in health inequality between racial/ethnic groups. Asian curve strictly dominates the others, while AIAN curve is strictly dominated by the others. These indicate that AIAN is the most unequal at all percentiles, while Asian is the least. Therefore, the differences between racial/ethnic groups are not only in terms of average quality of health but also in terms of health distribution itself among individuals within each group.

4.3.2. Geography of health inequality

Figure 7 presents health Gini coefficients for each region. North Country, Bronx County, Richmond County, and Southern Tier represent the darkest area indicating the highest health inequality, while the brightest areas are represented by - from the lowest inequality to the highest - Nassau, Westchester, and Rockland. Comparing Figures 4 and 7, it is clear that regions in dark areas in Figure 4 tend to be in dark areas in Figure 7. In the other words, regions with lower quality of health tend to have higher health inequality as plotted in Figure 8 for the 17 regions of New York State. The simple correlation coefficient between them is –0.83 and is statistically significant. Three worst regions in terms of both health inequality and quality of health are North Country (4), Bronx County (9), and Richmond County (14). It is interesting that North Country has very high rates of medical risk factors like diabetes, obesity and asthma, but the percentage of minority population is very small. On the other hand, three best regions are Nassau County (11), Westchester County (17), and Rockland County (15) where a very high average quality of health is achieved with very low health inequality. Interestingly, these three regions have rather high percentage of blacks in the population (see Figure 3).

For more detailed on information about the magnitude and significance of the, The 95%-confidence intervals on estimated health Gini coefficients across the regions are presented in Figure 9. All coefficients are significantly different from zero, indicating health inequality exists within each region. The statistical significance of the differences in health Gini coefficients between regions can be seen by comparing their confidence intervals. For instance, Nassau County has significantly a lower coefficient than those of the other regions with the exception of Westchester and Rockland Counties.

An important public policy question is: what are the main factors contributing to the inequality within each racial/ethnic group or each region? This can be answered by decomposing the health inequality into its determinants, as presented in the next section.

4.3.3. Decomposition analysis of health inequality

Decomposition analysis demonstrates differences in the components of inequalities for different racial/ethnic groups as well as for different regions. We are interested in analyzing health inequality attributable to socio-demographic factors including age, sex, race/ethnicity, marital status, education, employment status, health insurance, smoking status, access a doctor, and living in New York City. Among all these factors, the contributions of major variables by racial/ethnic groups are presented in Table 5 and the contributions by regions are presented in Table 6.

For the overall New York State population, among the socio-demographic variables, three most important factors contributing to health inequality are employment status, annual household income, and age. Each of these three factors contributes more than 20% to health inequality in the New York State population. Our estimate of the effect of income is similar to that in Wagstaff and van Doorslear (2004) who found that the contribution of income is around 25% of overall health inequality in the Canadian population. However, we find that income is relatively less important for the disadvantaged minority groups (*viz*., Black, Hispanic and AIAN). For instance, the corresponding percentage for AIAN is 11%, while for White it is 24%. The observed association between income inequality and health inequality on the one hand, and between health inequality and average health on the other found in this paper implies a "pollution effect" of income inequality on average health across regions, *cf*. Subramanian and Kawachi (2004). The correlation between income inequality and average health in our sample of the New York State regions was found to be -0.87.

If health status were distributed equally across different employment status, household incomes, and age groups, health inequality attributable to the socio-demographic variables in New York State population would be 66 percent lower. After controlling for other factors, race/ethnicity contributes only 4.5% to health inequality. As can be seen from Table A3 in the Appendix, race/ethnicity is highly intertwined with employment status, income, and education - Black, Hispanic, and AIAN have lower education levels, employment rates, and household incomes compared to those of White. That is why separate analysis for each group is necessary.

The pattern of the contributions of the socio-demographic variables varies considerably between racial/ethnic groups. The largest contributor to health inequality within the White population is Age (28%) followed by employment status (24%); for Black it is employment status (33%) followed by age (20%); for Hispanic it is employment status (32%) followed by education (23%); for Asian it is annual household income (32%) followed by age (18%); and for AIAN it is employment status (50%) followed by age (18%). Since inequality in employment status has the highest contribution to health inequality within Black, Hispanic, and AIAN, the most effective public policy initiative to eliminate health inequality within those groups is to ensure employment opportunities to all in these minority groups, particularly the AIAN. Education is another important factor, but it is more important for Hispanic. Interestingly, for Asian, income is the most important (32%) contributor to its health inequality.

Comparing across regions, the contribution of each factor to health inequality varies noticeably (see Table 6). For example, the contribution of employment status to health inequality ranges from 14% (Suffolk) to 42% (North Country). Thus, the most effective policy to eliminate health inequality in North Country is to provide employment opportunities to disadvantage population in North Country. The next most effective policy is to provide better health care to older population and to ensure good access to education and health care without discriminating by income levels. Moreover, in general the contributions of race/ethnicity to health inequality in Downstate regions are higher than those in Upstate regions. This is an expected result given the diversity of Downstate population.

5. Conclusions

Following recent developments in economic and socio-demographic research on health inequality, we use self-assessed health status conditioned by several objective determinants as a comprehensive measure of individual health. Among racial/ethnic groups, AIANs followed by Hispanics have the lowest average quality of health, while after adjusting for age distributions Hispanics have the lowest average quality of health. Asians have the highest average followed by Whites, while after adjusting for age distributions Whites have the best quality of health. This result highlights that when comparing quality of health between groups of populations, one needs to consider the age distribution within each group. Across the 17 regions of New York State, Bronx County followed by Richmond County and North Country has the lowest average quality of health, and Nassau County followed by Suffolk and Rockland Counties has the highest. These differences are mostly statistically significant.

We find statistically different health inequality, both spatially and between racial/ethnic groups. The highest health inequality is found within the AIAN group followed by Hispanic, while the lowest health inequality is found within the Asian group, followed by White. Across the 17 New York State regions, the highest health inequality is found in North Country followed by Bronx and Richmond Counties, while the lowest health inequality is found in Nassau County followed by Westchester and Rockland Counties. Groups with lower average quality of health tend to have higher health inequality.

The statistical decomposition analysis shows the contribution of several socio-economic and demographic factors to health inequality for different racial/ethnic groups as well as for different regions. After controlling for age distribution, the three major factors generating health inequality are employment, education, and household income - each contributing around 20% to the health inequality. For the disadvantaged minorities (Black, Hispanic, and AIAN), employment status is the most important factor - alone responsible for more than 30% of health inequality. The contribution of the three major factors varies across regions, but employment status is again found to be relatively more important. For instance, in North Country, 42% of its health disparity related to socio-demographic factors is explained by employment.

Our results underscore the need for different public health policy initiatives for different racial/ethnic groups and different regions to eliminate overall health disparity. In general, policies that can ensure equality in employment opportunities, educational access, and income will have a substantial impact on improving the average quality of health and in reducing health inequality. Unfortunately, there is no quick fix.

Table 1. Missing Data Pattern in New York State BRFSS Sample

Variable	Year					
	1999	2000	2001	2002	2003	2004
Could not afford to see a doctor	√	√	.	.	√	√
Participate in any physical activities or exercises	.	√	√	√	√	√
Fruit and vegetable servings per day	.	√	.	√	√	.
Heavy drinking	√	.	√	√	√	√
Activities limited due to health problem	.	√	√	.	√	√
Ever had asthma	.	√	√	√	√	√
Ever told blood pressure high	√	.	√	.	√	.
Ever told had coronary heart disease	√	.	√	.	√	.
Ever told had myocardial infarction	√	.	√	.	√	.
Ever told had stroke	√	.	√	.	√	.
Ever told had arthritis	.	√	√	√	√	√
Ever told blood cholesterol high	√	.	√	.	√	.
Had pain, aching, stiffness, and swelling	.	√	√	.	.	.
Participate in phys. activities or exercises	.	√	√	√	√	√
Fruit and vegetable servings per day	.	√	.	√	√	.

Note: √ means the information was collected.

Table 2. Coefficient Estimate of the Ordered Probit Model

Variable	Coefficient Estimate	Standard Error	P-value
Intercept	4.0997	0.1629	0.0000
Age 25-29	0.1848	0.0567	0.0011
Age 30-34	0.1662	0.0532	0.0018
Age 35-39	0.1028	0.0545	0.0593
Age 40-44	0.0531	0.0529	0.3148
Age 45-49	0.0814	0.0552	0.1404
Age 50-54	0.0088	0.0576	0.8784
Age 55-59	0.0532	0.0608	0.3811
Age 60-64	0.0130	0.0680	0.8478
Age 65-69	-0.1666	0.0739	0.0243
Age 70-74	-0.1162	0.0755	0.1236
Age 75-79	-0.3492	0.0842	0.0000
Age 80-84	-0.3112	0.0939	0.0009
Age >=85	-0.5571	0.1275	0.0000
Sex (male=1)	-0.0373	0.0239	0.1182
Black	-0.1423	0.0418	0.0007
Hispanic	-0.4037	0.0447	0.0000
Asian	-0.4191	0.0693	0.0000
AIAN	-0.1585	0.1451	0.2748
Other	-0.2822	0.0857	0.0010
Marital status	-0.0501	0.0240	0.0370
Body mass index/27	-0.6948	0.0614	0.0000
Grades 9 - 11 (Some high school)	0.3806	0.0843	0.0000
Grade 12 or GED (High school graduate)	0.5138	0.0762	0.0000
College 1 year to 3 years (Some college or technical school)	0.6270	0.0778	0.0000
College 4 years or more (College graduate)	0.7991	0.0793	0.0000
Self-employed	0.2432	0.0396	0.0000
Out of work	0.0186	0.0508	0.7136
A homemaker	-0.0158	0.0463	0.7335
A student	0.1424	0.0658	0.0306
Retired	-0.0979	0.0463	0.0343
Unable to work	-0.4573	0.0652	0.0000
Having health plan	0.1101	0.0399	0.0058
Annual Household Income ($1,000)	0.0048	0.0004	0.0000
Smoking	-0.2418	0.0275	0.0000
Participating in any physical activities or exercises	0.3076	0.0289	0.0000
Fruit and vegetable servings per day	0.0424	0.0072	0.0000
Number of days physical health not good	-0.0595	0.0025	0.0000
Number of days mental health not good	-0.0157	0.0016	0.0000
Ever told had diabetes	-0.7772	0.0543	0.0000

Could not afford to see doctor	-0.3063	0.0469	0.0000
Heavy drinking	0.0439	0.0338	0.1957
Activities limited due to health problem	-0.6144	0.0392	0.0000
Ever had asthma	-0.2065	0.0348	0.0000
Ever told blood pressure high	-0.3967	0.0299	0.0000
Ever told had coronary heart disease	-0.4685	0.0721	0.0000
Ever told had myocardial infarction	-0.4392	0.0894	0.0001
Ever told had stroke	-0.3093	0.0838	0.0004
Ever told had arthritis	-0.1240	0.0319	0.0002
Ever told blood cholesterol high	-0.2090	0.0271	0.0000
Had pain, aching, stiffness or swelling in or around a joint	-0.2228	0.0386	0.0001
Dummy for NY City	-0.1934	0.0266	0.0000
Threshold 2	1.7705	0.0618	0.0000
Threshold 3	3.6140	0.1100	0.0000
Threshold 4	5.2001	0.1531	0.0000
McKelvey-Zavoina R^2 = 0.60			

Note: Reference for Age group dummies is 18-24; for Education it is grade 8 or less; and for Employment status it is employed for wage.

Table 3. Coefficient Estimate of the Heteroskedasticity Scale Function

	Coefficient Estimate	Standard Error	P-value
Sex (male=1)	0.2084	0.0544	0.0002
Age 25-29	0.1109	0.1276	0.3851
Age 30-34	-0.0662	0.1386	0.6336
Age 35-39	-0.0365	0.1342	0.7861
Age 40-44	-0.0735	0.1342	0.5843
Age 45-49	0.0519	0.1251	0.6784
Age 50-54	0.1943	0.1236	0.1161
Age 55-59	0.2911	0.1230	0.0180
Age 60-64	0.4317	0.1208	0.0004
Age 65-69	0.2825	0.1471	0.0573
Age 70-74	0.2632	0.1429	0.0660
Age 75-79	0.4133	0.1461	0.0048
Age 80-84	0.2888	0.1809	0.1116
Age >=85	0.8155	0.1737	0.0000
Black	0.3716	0.0818	0.0000
Hispanic	0.4014	0.0810	0.0000
Asian	0.3521	0.1505	0.0198
AIAN	0.6897	0.2313	0.0029
Annual Household Income ($1,000)	-0.0024	0.0009	0.0067
Having health plan	-0.2058	0.0794	0.0096
Education higher than high school	-0.1035	0.0574	0.0717
Sex (male=1)	0.2084	0.0544	0.0002

Table 4. Average Quality of Health and
Health Adjusted Life Expectancy (HALE)

		All	White	Black	Hispanic	Asian	AIAN
Average quality of health		0.750	0.765	0.715	0.678	0.778	0.665
Age	Life expectancy	HALE (in year)					
20-24	58.23	43.05	44.24	40.23	36.81	43.75	37.52
25-29	53.50	39.35	40.44	36.62	33.40	40.05	33.74
30-34	48.74	35.52	36.48	32.90	29.87	36.19	30.33
35-39	44.00	31.68	32.51	29.22	26.35	32.33	26.73
40-44	39.33	27.97	28.69	25.66	23.02	28.65	23.28
45-49	34.78	24.41	25.02	22.30	19.90	25.11	20.23
50-54	30.36	20.99	21.48	19.15	16.99	21.68	17.82
55-59	26.09	17.76	18.16	16.17	14.28	18.48	15.27
60-64	22.01	14.74	15.05	13.47	11.85	15.30	12.77
65-69	18.19	11.96	12.16	10.95	9.68	12.58	10.17
70-74	14.69	9.56	9.68	8.77	7.87	10.61	8.11
75-79	11.54	7.39	7.48	6.75	6.07	8.38	6.13
80-84	8.79	5.63	5.70	5.22	4.69	6.34	4.86

Table 5. Decomposition of Health Inequality by Racial/Ethnic Groups

Variable		Race/ethnicity					
		All	White	Black	Hisp.	Asian	AIAN
Age	(%)	21.63	28.46	19.94	16.91	18.04	18.51
Race/ethnicity	(%)	4.53	-	-	-	-	-
Education	(%)	17.13	15.74	17.32	22.73	17.24	12.47
Employment status	(%)	24.51	24.11	32.98	31.58	15.23	49.66
Annual household Income ($1,000)	(%)	22.44	23.79	17.26	14.92	31.56	11.01
Smoking	(%)	3.16	3.51	5.01	2.73	2.94	4.45
Could not afford to see doctor	(%)	6.42	5.21	7.11	10.10	13.78	4.71

Note: Variables with small contributions are not presented in this table.

Table 6. Decomposition of Total Health Inequality by Regions

Region	Contribution of each factor to health inequality (%)						
	Age	Race/Ethnicity	Education	Employment	Income	Smoking	Could not afford to see doctor
Hudson Valley	22.7	2.6	16.4	23.2	24.3	3.4	7.1
Capital Region	27.3	1.8	16.6	19.2	23.9	4.0	5.8
Mohawk	25.5	1.6	15.0	27.3	19.0	3.5	6.3
N Country	18.2	0.8	12.9	42.3	15.4	4.3	6.4
Central NY	26.9	1.3	13.9	26.8	21.0	3.8	5.4
Southern Tier	25.2	1.3	14.1	29.4	17.0	4.8	7.5
Western NY	27.3	1.7	16.1	25.7	20.1	3.4	5.1
Finger Lakes	25.5	2.5	17.3	19.6	23.6	4.3	6.4
Bronx	18.8	4.3	13.6	31.8	14.4	3.1	7.3
Kings	17.7	6.9	17.6	23.5	19.5	2.7	7.2
Nassau	18.8	8.1	17.2	19.4	24.0	2.4	6.6
New York	22.3	5.5	16.8	20.1	20.6	2.5	8.7
Queens	20.0	4.1	12.3	27.8	23.4	2.8	8.1
Richmond	24.8	2.9	16.1	20.0	25.5	4.0	5.7
Rockland	27.8	2.5	17.6	16.8	26.4	2.6	5.0
Suffolk	23.5	5.0	18.7	14.3	27.5	2.8	6.2
Westchester	18.2	3.6	17.7	19.8	26.6	2.8	9.2

Note: Small contributors are not presented in this table.

Figure 1. Lorenz Curve

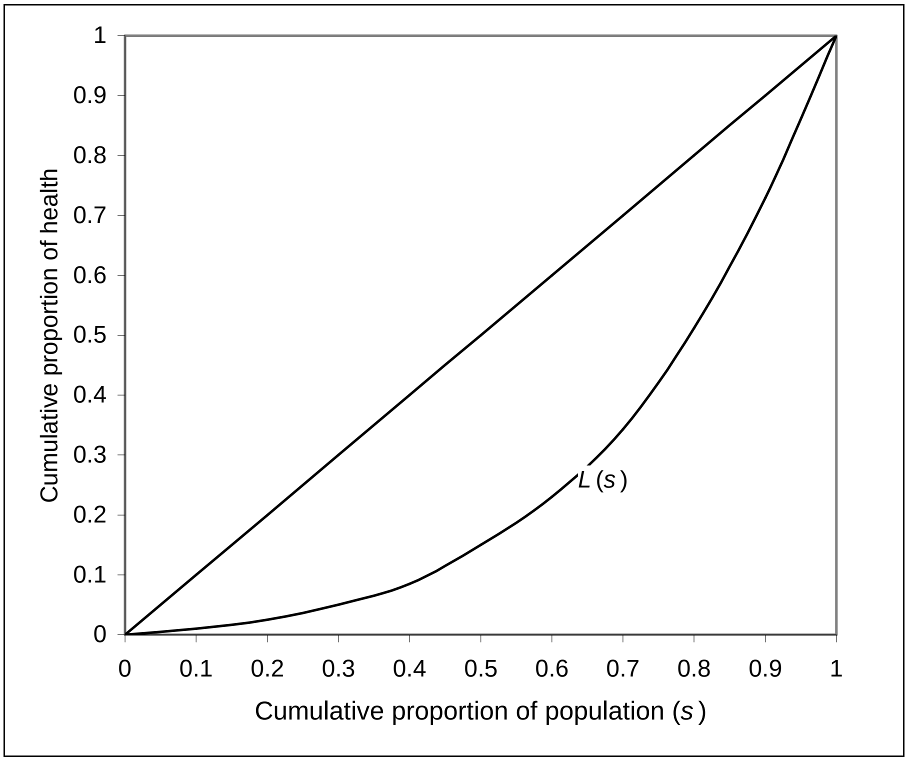


Figure 2. Income Inequality

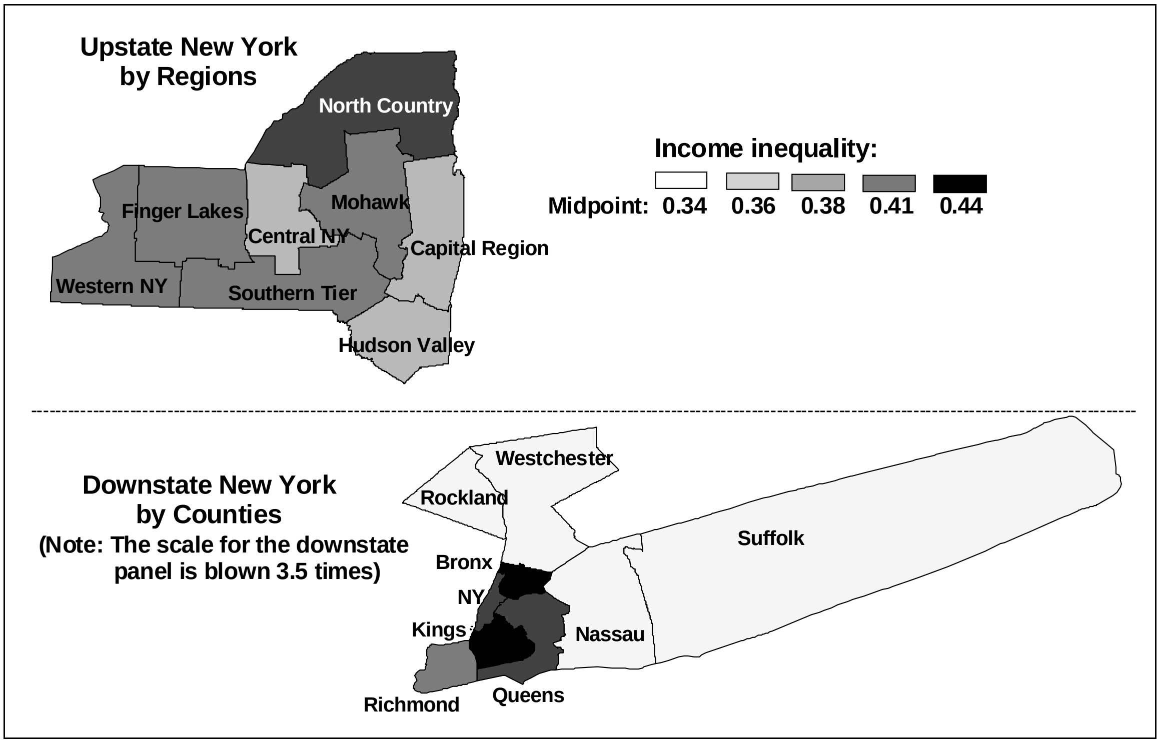


Figure 3. Percent Black Population

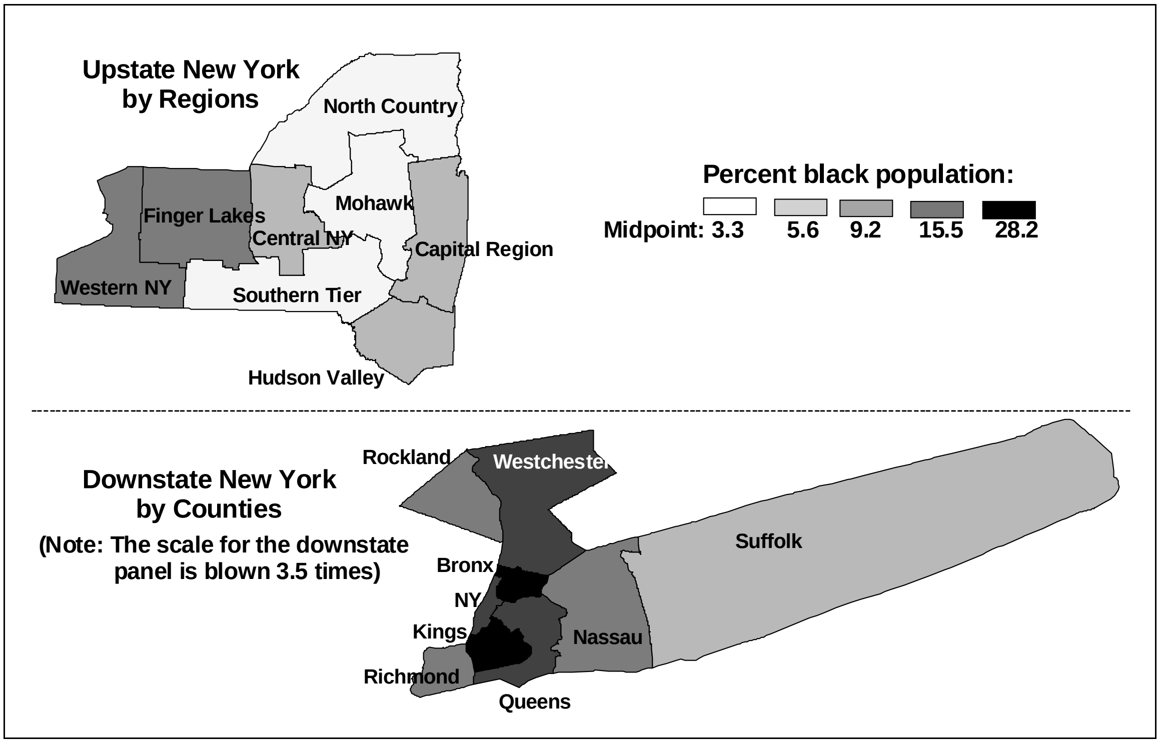


Figure 4. Average Quality of Health by Regions

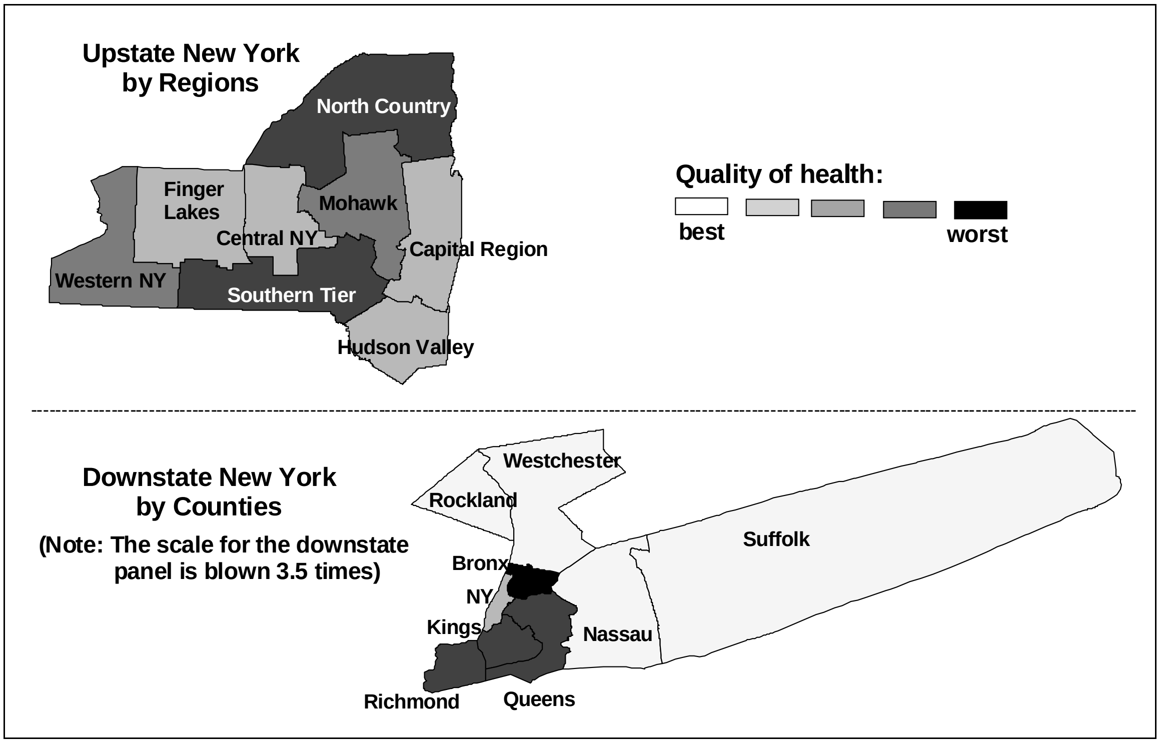


Figure 5. Health Gini Coefficient with Corresponding 95%-Confidence Interval by Racial/Ethnic Groups

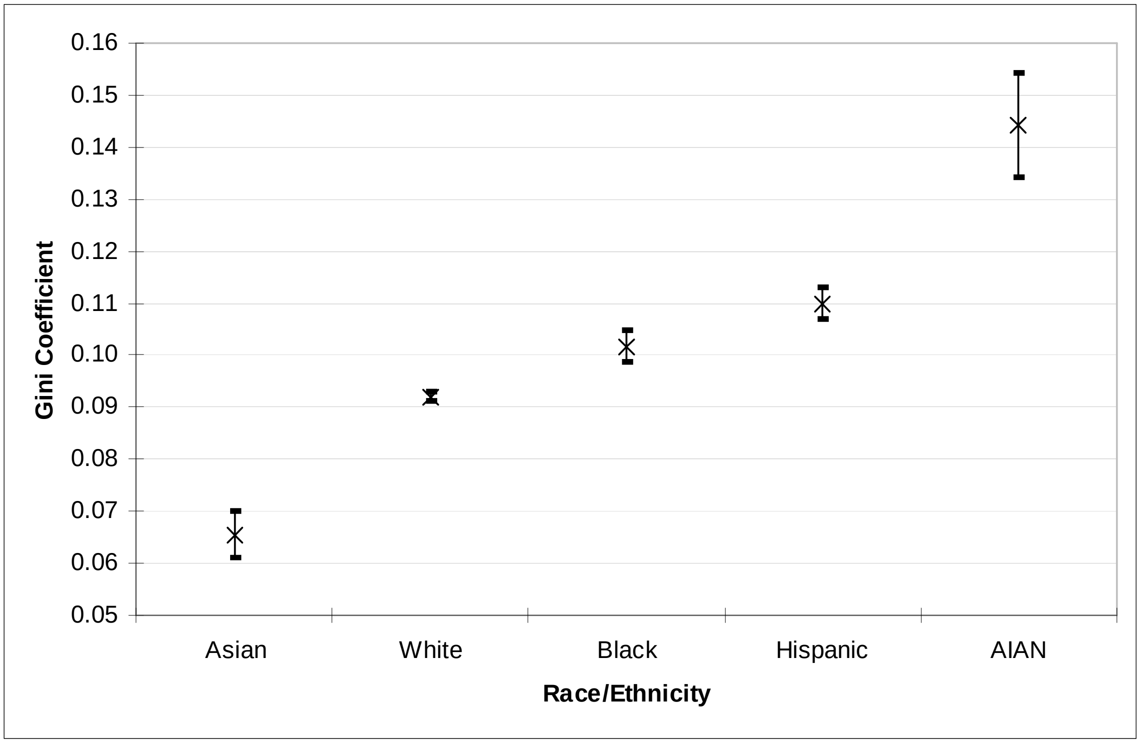


Figure 6. Health Lorenz Curve by Racial/Ethnic Groups

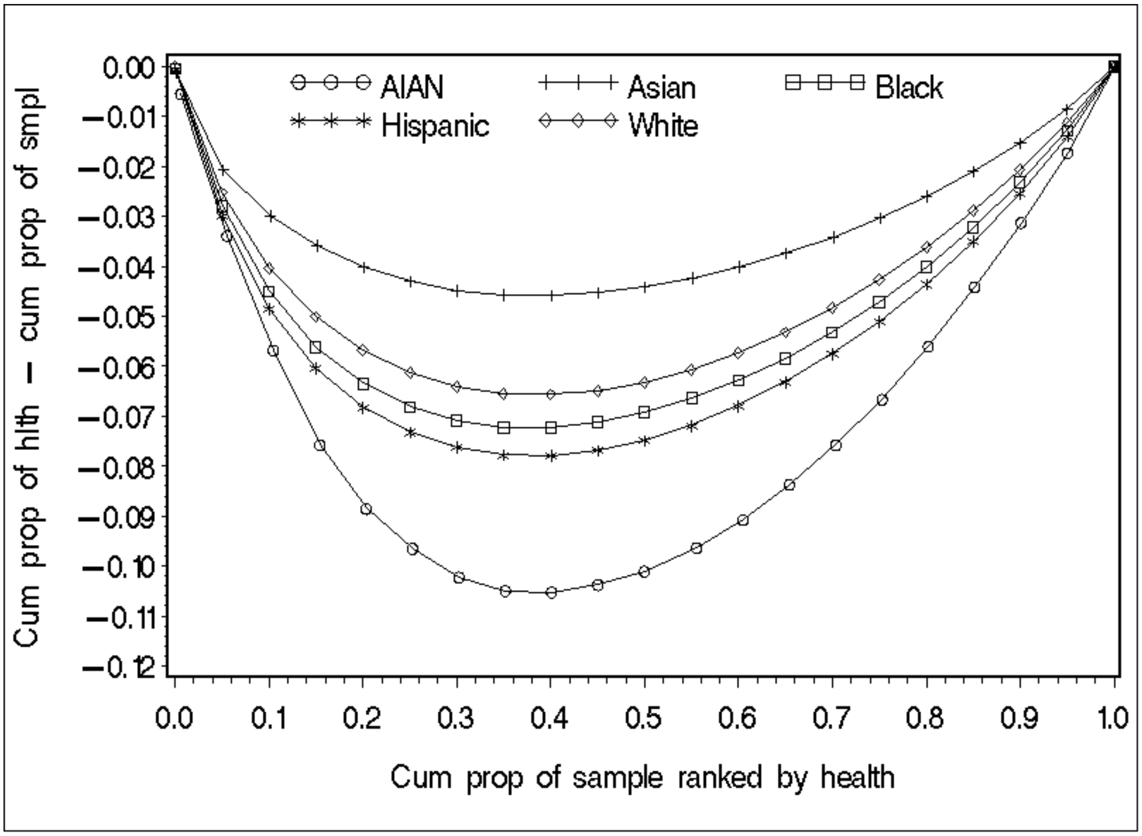


Figure 7. Health Inequality by Regions

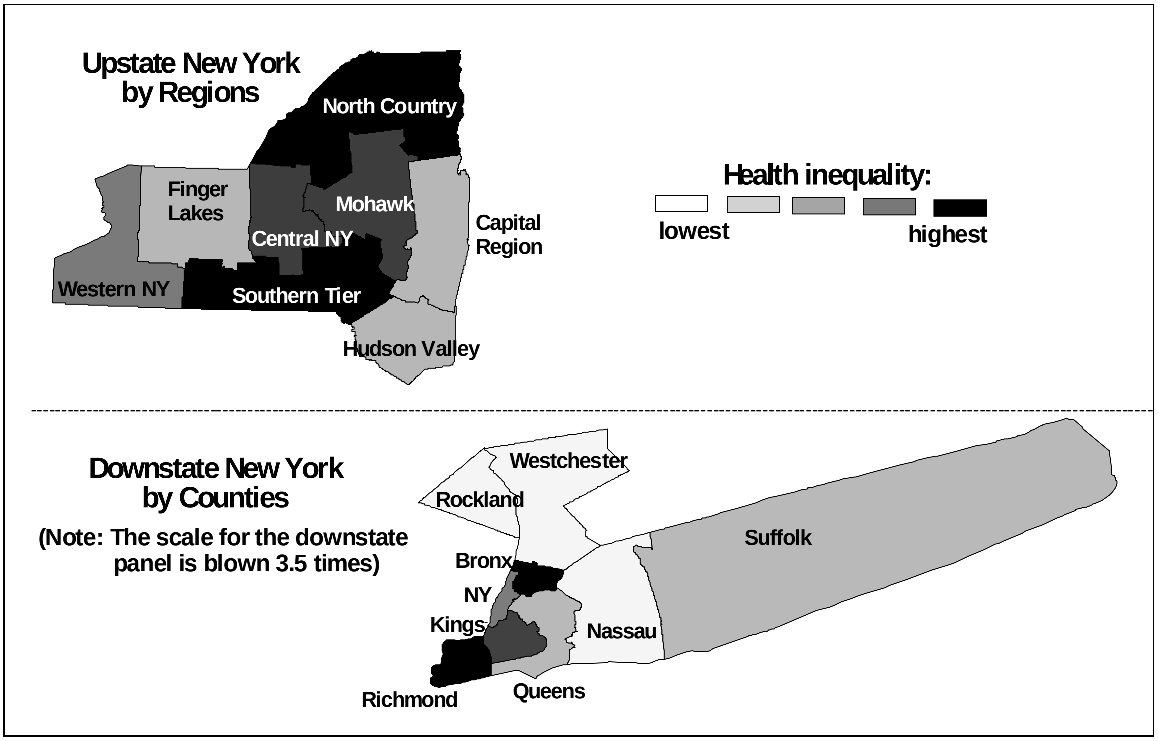
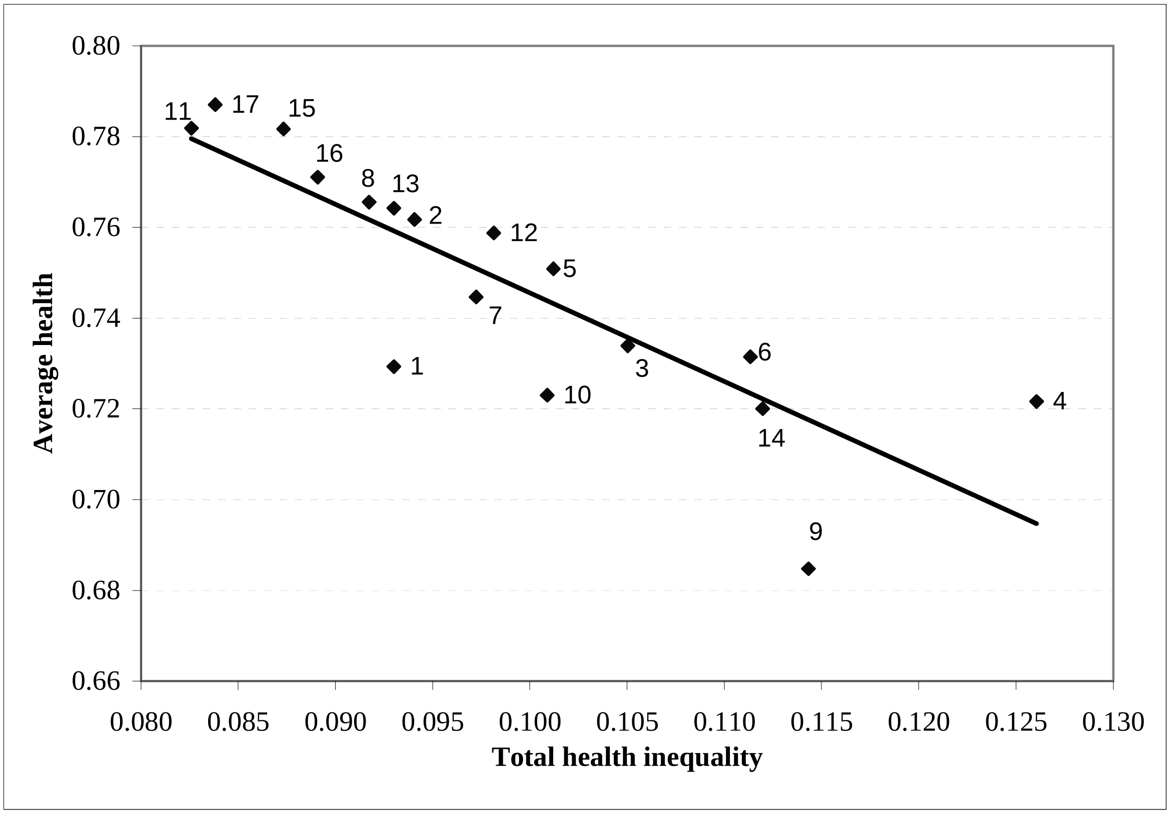
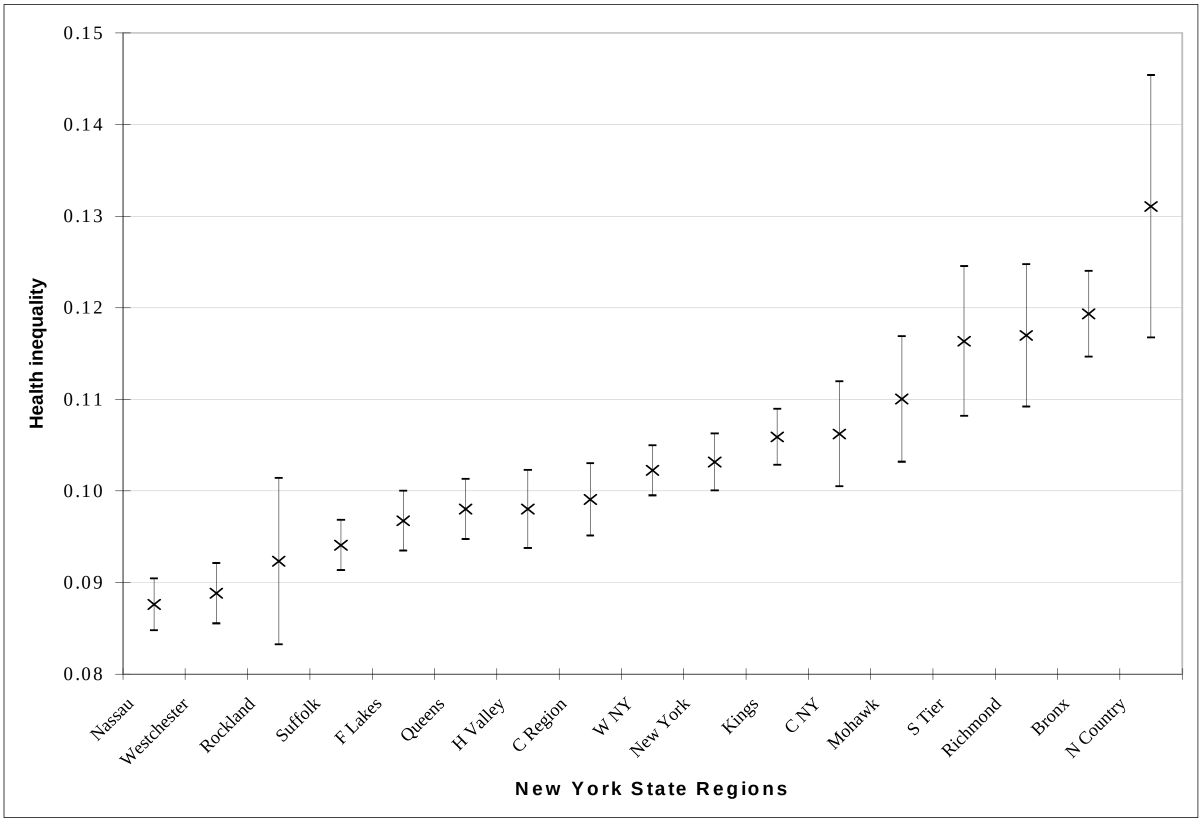


Figure 8. Average Health *vs.* Total Health Inequality



Note: 1 - Hudson Valley; 2 - Capital Region; 3 - Mohawk; 4 - North Country; 5 - Central New York; 6 - Southern Tier; 7 - Western New York; 8 - Finger Lakes; 9 - Bronx County; 10 - Kings County; 11 - Nassau County; 12 - New York County; 13 – Queens County; 14 – Richmond County; 15 – Rockland County; 16 - Suffolk County; 17 - Westchester County.

Figure 9. Health Gini Coefficient with 95%-Confidence Interval by Regions



APPENDIX

Multiple imputation

The basic idea of the multiple-imputations is to create two or more completed datasets using the correlation structure of the available covariates, and then analyzing each completed dataset. Subsequently, we make inferences based on both within and between variability of the estimates obtained from the completed datasets.

In this method, the missing values are filled in by drawing random samples from the conditional distribution of missing values given the observed values. Assuming the joint distribution of the variables is multivariate normal, and using Markov Chain Monte Carlo (MCMC) method to obtain simulation-based estimates of the posterior parameters of the distribution, values from the conditional distribution for the missing values are drawn randomly given the observed values.

The performance of the multiple-imputation method can be seen in our case by comparing the descriptive statistics of the imputed variables before and after imputation, as presented in Table A1. The table shows that the mean and standard deviation of each variable before and after imputation are almost the same. Since the "missingness" does not depend on any variables in the dataset, the missing values are considered to be *missing completely at random* (MCAR). The MCAR characteristic of the missing values implies that the statistics obtained from incomplete data are unbiased. Since the statistics obtained from the imputed datasets are almost the same as those obtained from the incomplete (original) dataset, the statistics obtained from the imputed datasets are also unbiased. See also Horton et al. (2003).

Table A1. Mean and Standard Deviation based on Original and Imputed Datasets

Variable	Original dataset		Imputed dataset		Ratio	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of days physical health not good	3.562	8.002	3.578	8.011	1.004	1.001
Number of days mental health not good	3.317	7.501	3.322	7.501	1.001	1.000
Ever told had diabetes	0.070	0.256	0.070	0.256	1.000	1.000
Annual Household Income ($1,000)	50.243	37.202	49.361	37.298	0.982	1.003
Could not afford to see doctor	0.113	0.316	0.113	0.316	1.000	1.000
Heavy drinking	0.133	0.340	0.134	0.340	1.005	1.000
Activities limited due to health problem	0.189	0.391	0.185	0.390	0.979	0.996
Ever had asthma	0.119	0.324	0.119	0.324	0.998	1.000
Ever told blood pressure high	0.276	0.447	0.280	0.447	1.013	1.001
Ever told had coronary heart disease	0.049	0.217	0.048	0.216	0.968	0.997
Ever told had myocardial infarction	0.043	0.204	0.042	0.203	0.959	0.997
Ever told had stroke	0.026	0.158	0.024	0.158	0.931	0.999
Ever told had arthritis	0.280	0.449	0.281	0.449	1.004	1.001
Ever told blood cholesterol high	0.324	0.468	0.304	0.469	0.937	1.001
Had pain, aching, stiffness or swelling	0.420	0.494	0.443	0.498	1.056	1.008
Participate in phys. activities or exercises	0.754	0.431	0.754	0.430	1.000	1.000
Fruit and vegetable servings per day	3.855	2.192	3.862	2.191	1.002	1.000

Table A2. Regions of New York State

Upstate by Economic Development Regions		
1 Hudson Valley	4 North Country	7 Western New York
Dutchess	Clinton	Allegany
Orange	Essex	Cattaraugus
Putnam	Franklin	Chautauqua
Sullivan	Jefferson	Erie
Ulster	Lewis	Niagara
	St. Lawrence	
2 Capital Region		8 Finger Lakes
Albany	5 Central New York	Genesee
Columbia	Cayuga	Livingston
Greene	Cortland	Monroe
Rensselaer	Madison	Ontario
Saratoga	Onondaga	Orleans
Schenectady	Oswego	Seneca
Warren		Wayne
Washington	6 Southern Tier	Wyoming
	Broome	Yates
3 Mohawk	Chemung	
Fulton	Chenango	
Hamilton	Delaware	
Herkimer	Otsego	
Montgomery	Schuyler	
Oneida	Steuben	
Schoharie	Tioga	
	Tompkins	
Downstate by Counties		
9 Bronx	12 New York	15 Rockland
10 Kings	13 Queens	16 Suffolk
11 Nassau	14 Richmond	17 Westchester

Table A3. Descriptive Statistics by Racial/Ethnic Groups

Variables	Race/Ethnicity						
	All	White	Black	Hisp.	Asian	AIAN	Other
Reported age in years	45.44	47.57	43.75	39.88	38.57	44.19	43.31
Gender (male=1)	0.488	0.489	0.435	0.476	0.590	0.545	0.595
Marital status	0.541	0.591	0.371	0.463	0.590	0.446	0.475
Education:							
Grade 8 or less	0.040	0.012	0.045	0.159	0.017	0.065	0.036
Grades 9 - 11 (Some high school)	0.072	0.047	0.100	0.165	0.019	0.184	0.047
Grade 12 or GED (High school graduate)	0.294	0.294	0.345	0.286	0.153	0.353	0.291
College 1 year to 3 years	0.259	0.266	0.289	0.217	0.197	0.270	0.263
College 4 years or more	0.336	0.380	0.221	0.173	0.614	0.127	0.363
Employment:							
Employed for wages	0.555	0.545	0.568	0.570	0.647	0.487	0.512
Self-employed	0.081	0.087	0.055	0.075	0.077	0.061	0.123
Out of work for more than 1 year	0.020	0.014	0.038	0.028	0.015	0.026	0.029
Out of work for less than 1 year	0.035	0.027	0.058	0.050	0.029	0.038	0.061
A homemaker	0.064	0.066	0.033	0.092	0.050	0.053	0.040
A student	0.045	0.039	0.049	0.049	0.119	0.034	0.057
Retired	0.159	0.194	0.130	0.070	0.048	0.160	0.103
Unable to work	0.041	0.028	0.070	0.067	0.016	0.140	0.076
Annual Household Income ($1,000)	55.71	62.21	42.74	36.74	62.47	34.39	48.05
Have health plan	0.860	0.914	0.836	0.685	0.787	0.755	0.765
Could not afford to see a doctor	0.110	0.078	0.141	0.209	0.114	0.182	0.200
Smoking	0.221	0.228	0.219	0.204	0.132	0.343	0.248
Heavy drinking	0.165	0.178	0.108	0.161	0.113	0.179	0.195
Self-assessed health status:							
Excellent	0.225	0.246	0.183	0.162	0.257	0.173	0.197
Very good	0.333	0.367	0.283	0.238	0.331	0.175	0.328
Good	0.298	0.273	0.356	0.346	0.322	0.381	0.287
Fair	0.110	0.084	0.138	0.205	0.064	0.158	0.127
Poor	0.035	0.030	0.039	0.048	0.026	0.113	0.061
Number of days physical health not good	3.343	3.264	3.632	3.765	1.650	5.362	3.478
Number of days mental health not good	3.227	3.039	3.483	3.783	2.468	5.131	4.297
Activities limited due to health problem	0.162	0.175	0.147	0.138	0.064	0.309	0.155
Body mass index (BMI)	26.48	26.23	28.05	27.00	23.97	27.61	25.81
Fruit and vegetable servings per day	4.032	4.031	3.914	3.938	4.287	4.280	4.758
Participate in any exercises	0.745	0.786	0.686	0.619	0.747	0.677	0.732
Ever had asthma	0.118	0.113	0.139	0.133	0.059	0.177	0.124
Ever told blood pressure high	0.243	0.245	0.302	0.221	0.122	0.312	0.195
Ever told had coronary heart disease	0.042	0.044	0.042	0.035	0.020	0.070	0.046
Ever told had myocardial infarction	0.035	0.038	0.026	0.032	0.000	0.076	0.022
Ever told had stroke	0.019	0.019	0.024	0.020	0.004	0.060	0.014
Ever told had diabetes	0.064	0.055	0.105	0.070	0.047	0.116	0.085
Ever told had arthritis	0.251	0.290	0.213	0.163	0.081	0.351	0.177
Had pain in or around a joint	0.383	0.417	0.310	0.316	0.237	0.525	0.466
Ever told blood cholesterol high	0.310	0.323	0.245	0.280	0.348	0.483	0.266

Source: Calculated from BRFSS 1999-2004

Table A4. Descriptive Statistics by Regions

Variable	Upstate Regions								Downstate Regions								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
Reported age in years	45.340	47.33	49.49	44.19	47.50	45.03	46.18	45.64	43.05	42.54	47.91	44.67	43.02	45.02	45.62	46.40	47.12
Gender (male=1)	0.497	0.465	0.458	0.528	0.501	0.521	0.497	0.455	0.452	0.463	0.498	0.494	0.508	0.496	0.487	0.483	0.500
Marital status	0.594	0.576	0.556	0.573	0.591	0.552	0.565	0.569	0.402	0.421	0.610	0.352	0.506	0.557	0.719	0.627	0.622
Education:																	
Grade 8 or less	0.011	0.022	0.019	0.000	0.017	0.012	0.015	0.010	0.112	0.082	0.027	0.070	0.049	0.022	0.027	0.024	0.038
Grades 9 - 11 (Some high school)	0.069	0.052	0.080	0.076	0.042	0.081	0.048	0.065	0.148	0.110	0.042	0.073	0.091	0.045	0.028	0.048	0.058
Grade 12 or GED (High school graduate)	0.294	0.270	0.320	0.291	0.304	0.297	0.346	0.267	0.307	0.302	0.257	0.166	0.282	0.376	0.213	0.298	0.215
College 1 year to 3 years	0.286	0.289	0.324	0.384	0.276	0.325	0.291	0.278	0.239	0.208	0.249	0.175	0.272	0.258	0.240	0.257	0.228
College 4 years or more	0.341	0.368	0.257	0.249	0.360	0.286	0.300	0.380	0.195	0.298	0.424	0.516	0.308	0.300	0.492	0.373	0.462
Employment:																	
Employed for wages	0.591	0.566	0.530	0.647	0.561	0.567	0.580	0.587	0.538	0.557	0.535	0.487	0.556	0.531	0.584	0.560	0.563
Self-employed	0.081	0.063	0.071	0.031	0.044	0.047	0.056	0.062	0.048	0.085	0.083	0.142	0.079	0.067	0.154	0.101	0.096
Out of work for more than 1 year	0.015	0.014	0.017	0.005	0.021	0.010	0.017	0.021	0.036	0.035	0.012	0.022	0.024	0.024	0.009	0.010	0.015
Out of work for less than 1 year	0.018	0.037	0.040	0.014	0.031	0.041	0.041	0.034	0.044	0.054	0.020	0.044	0.041	0.037	0.018	0.024	0.028
A homemaker	0.055	0.068	0.035	0.014	0.059	0.057	0.063	0.072	0.074	0.063	0.087	0.050	0.064	0.074	0.083	0.064	0.080
A student	0.039	0.041	0.035	0.044	0.044	0.051	0.032	0.040	0.056	0.046	0.041	0.058	0.073	0.058	0.014	0.038	0.038
Retired	0.160	0.188	0.212	0.133	0.201	0.180	0.171	0.157	0.133	0.108	0.199	0.143	0.123	0.138	0.114	0.175	0.168
Unable to work	0.041	0.023	0.062	0.113	0.040	0.048	0.042	0.027	0.072	0.053	0.023	0.055	0.040	0.072	0.025	0.028	0.013
Annual Household Income ($1,000)	64.119	60.37	50.90	46.86	59.48	47.44	51.27	58.13	37.65	44.58	74.14	60.50	48.77	62.19	75.83	70.13	72.90
Have health plan	0.900	0.911	0.849	0.837	0.900	0.854	0.921	0.906	0.775	0.773	0.918	0.848	0.765	0.907	0.885	0.890	0.876
Could not afford to see doctor	0.124	0.070	0.096	0.114	0.084	0.135	0.089	0.092	0.176	0.151	0.095	0.126	0.132	0.129	0.205	0.094	0.078
Smoking	0.247	0.232	0.229	0.283	0.233	0.275	0.259	0.223	0.194	0.209	0.195	0.202	0.181	0.284	0.167	0.223	0.152
Heavy drinking	0.150	0.196	0.178	0.231	0.179	0.225	0.195	0.193	0.129	0.127	0.126	0.193	0.140	0.147	0.146	0.190	0.139
Self-assessed health status:																	
Excellent	0.239	0.250	0.267	0.173	0.224	0.219	0.211	0.231	0.169	0.168	0.265	0.255	0.191	0.213	0.229	0.251	0.273
Very good	0.372	0.371	0.273	0.392	0.367	0.358	0.351	0.379	0.259	0.304	0.353	0.292	0.285	0.300	0.304	0.363	0.342
Good	0.275	0.258	0.288	0.307	0.290	0.280	0.316	0.292	0.334	0.344	0.260	0.281	0.350	0.286	0.335	0.262	0.262
Fair	0.077	0.091	0.144	0.071	0.083	0.097	0.098	0.076	0.163	0.148	0.107	0.138	0.136	0.134	0.105	0.096	0.090
Poor	0.037	0.031	0.028	0.057	0.036	0.046	0.024	0.021	0.074	0.036	0.016	0.034	0.038	0.067	0.027	0.029	0.033
Number of days physical health not good	3.101	3.299	4.264	3.244	3.414	3.692	3.617	3.104	4.081	3.183	2.665	3.479	3.092	4.231	2.617	3.390	2.784
Number of days mental health not good	3.492	2.874	3.391	1.303	2.822	4.019	3.259	3.011	4.194	3.160	2.558	3.895	3.345	3.374	3.530	3.153	2.951

Activities limited due to health problem	0.169	0.149	0.207	0.184	0.188	0.178	0.180	0.166	0.163	0.126	0.158	0.169	0.125	0.220	0.146	0.178	0.131
Body mass index (BMI)	26.947	26.45	26.46	27.90	26.84	26.54	26.83	26.54	27.47	26.94	26.14	25.29	26.01	26.65	26.78	26.39	25.77
Fruit and vegetable servings per day	4.003	4.037	3.822	4.204	4.159	3.765	4.075	4.058	4.012	4.031	4.114	4.192	3.892	3.639	3.784	4.017	4.280
Participate in any exercises	0.781	0.786	0.786	0.804	0.794	0.798	0.786	0.772	0.663	0.676	0.735	0.778	0.695	0.729	0.696	0.741	0.773
Ever had asthma	0.129	0.132	0.121	0.174	0.110	0.098	0.114	0.138	0.146	0.099	0.113	0.154	0.103	0.095	0.112	0.108	0.085
Ever told blood pressure high	0.277	0.283	0.335	0.320	0.261	0.275	0.254	0.244	0.216	0.230	0.241	0.209	0.225	0.259	0.268	0.244	0.233
Ever told had coronary heart disease	0.033	0.044	0.046	-	0.045	0.048	0.034	0.043	0.052	0.040	0.052	0.036	0.043	0.033	-	0.039	0.045
Ever told had myocardial infarction	0.043	0.024	0.045	-	0.053	0.038	0.033	0.028	0.039	0.026	0.042	0.032	0.028	0.043	0.044	0.026	0.022
Ever told had stroke	0.015	0.034	0.034	-	0.021	0.044	0.020	0.022	0.017	0.020	0.016	0.016	0.015	0.037	-	0.017	0.019
Ever told had diabetes	0.067	0.078	0.074	0.141	0.056	0.071	0.058	0.068	0.101	0.067	0.062	0.056	0.069	0.075	0.064	0.050	0.066
Ever told had arthritis	0.247	0.283	0.332	0.347	0.332	0.281	0.303	0.292	0.182	0.183	0.248	0.231	0.189	0.282	0.200	0.238	0.221
Had pain in or around a joint	0.371	0.366	0.382	-	0.437	0.384	0.467	0.466	0.356	0.290	0.320	0.430	0.301	0.372	0.380	0.407	0.356
Ever told blood cholesterol high	0.302	0.310	0.274	0.334	0.335	0.255	0.329	0.289	0.257	0.282	0.360	0.301	0.280	0.329	0.416	0.325	0.275

Source: Calculated from BRFSS 1999-2004

Note: 1 - Hudson Valley; 2 - Capital Region; 3 - Mohawk; 4 - North Country; 5 - Central New York; 6 - Southern Tier; 7 - Western New York; 8 - Finger Lakes; 9 - Bronx County; 10 - Kings County; 11 - Nassau County; 12 - New York County; 13 – Queens County; 14 – Richmond County; 15 - Rockland County;16 - Suffolk County; 17 - Westchester County.

Figure A1. Quality of Health
Based on Percentage of "Very good" and "Excellent" Health

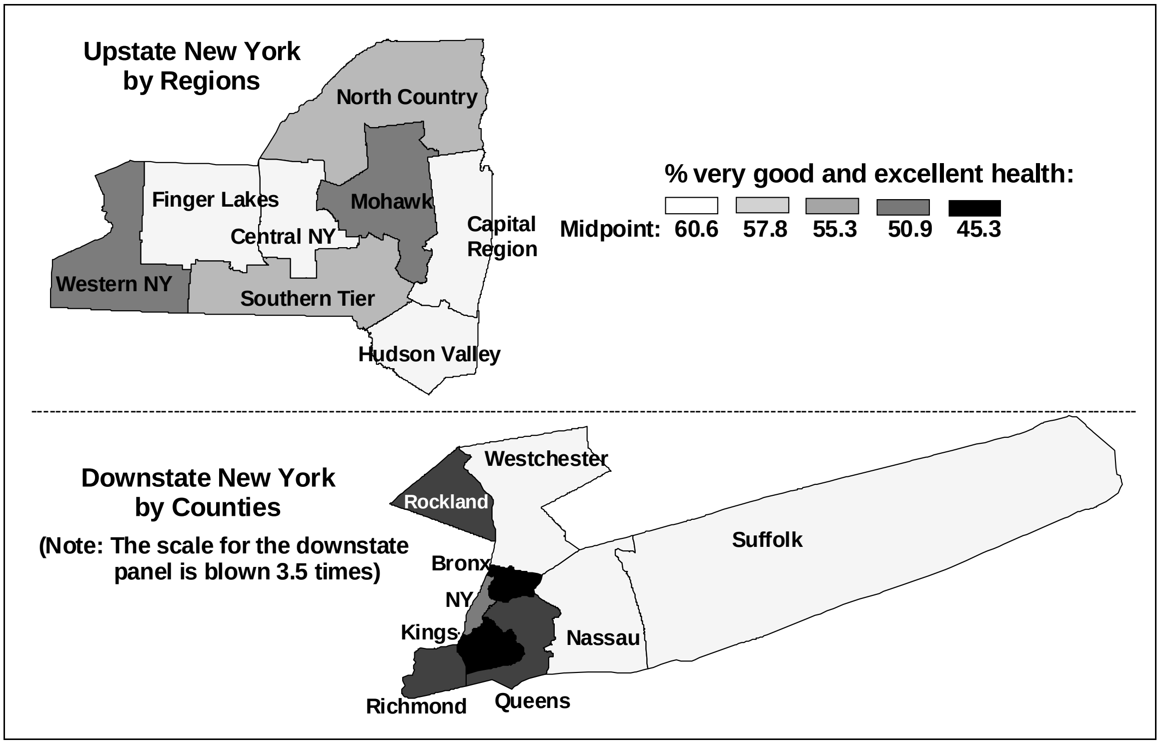
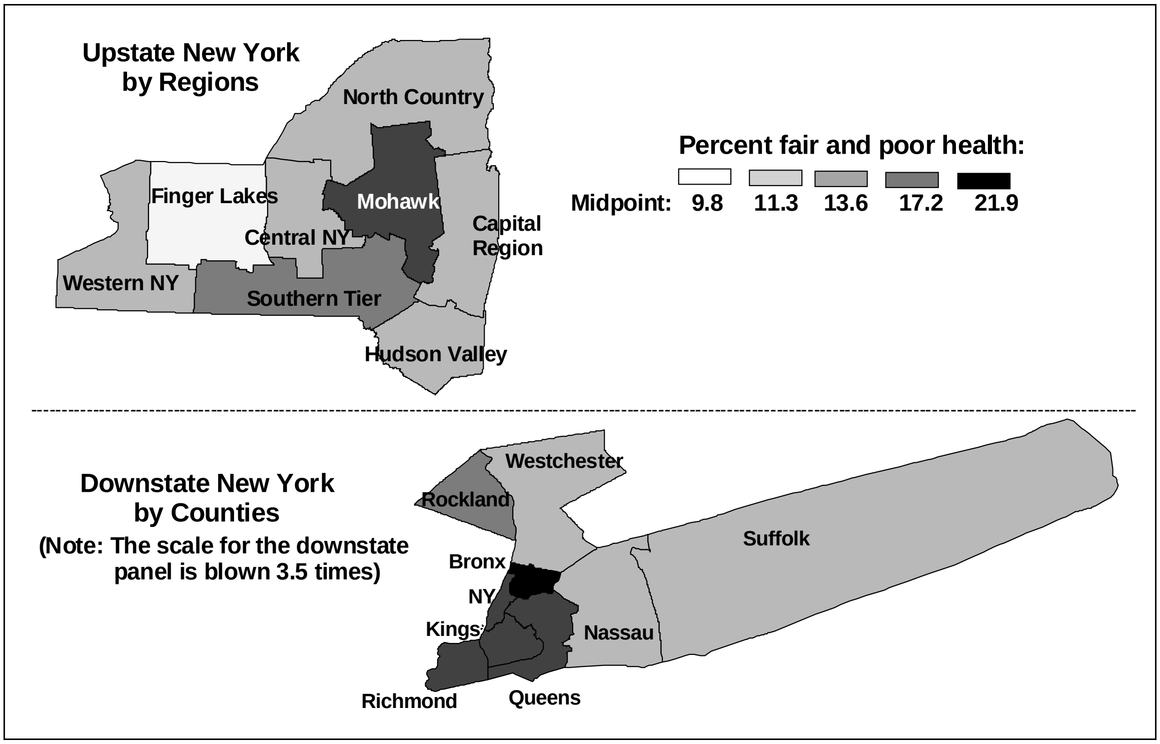


Figure A2. Quality of Health
Based on Percentage of "Fair" and "Poor" Health



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