NBER WORKING PAPER SERIES

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Working Paper 10365
http://www.nber.org/papers/w10365

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
March 2004

We are grateful to Elizabeth Weber and Florence Neymotin for outstanding research assistance, and to Thomas Lemieux, Guido Imbens, and participants in the RAND Health Economics Seminar for comments and suggestions. Funding was provided by a National Institute of Aging Grant through the Center for the Economics and Demography of Aging at UC Berkeley, and by the Center for Labor Economics at UC Berkeley. The views expressed herein are those of the authors and not necessarily those of the National Bureau of Economic Research.

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NBER Working Paper No. 10365
March 2004
JEL No. I12, I18

ABSTRACT

We use the increases in health insurance coverage at age 65 generated by the rules of the Medicare program to evaluate the effects of health insurance coverage on health related behaviors and outcomes. The rise in overall coverage at age 65 is accompanied by a narrowing of disparities across race and education groups. Groups with bigger increases in coverage at 65 experience bigger reductions in the probability of delaying or not receiving medical care, and bigger increases in the probability of routine doctor visits. Hospital discharge records also show large increases in admission rates at age 65, especially for elective procedures like bypass surgery and joint replacement. The rises in hospitalization are bigger for whites than blacks, and for residents of areas with higher rates of insurance coverage prior to age 65, suggesting that the gains arise because of the relative generosity of Medicare, rather than the availability of insurance coverage. Finally, there are small impacts of reaching age 65 on self-reported health, with the largest gains among the groups that experience the largest gains in insurance coverage. In contrast we find no evidence of a shift in the rate of growth of mortality rates at age 65.

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One fifth of non-elderly adults in the United States lacked health insurance in 2002.[1] Insured people are healthier than the uninsured, leading many analysts to conclude that access to health insurance is a public policy concern.[2] Nevertheless, credible evidence that insurance coverage causes better health is limited (Levy and Meltzer, 2001). Insured and uninsured people exhibit many behavioral differences that are correlated with health, including diet, smoking, exercise, and seatbelt use.[3] Moreover, both the supply and demand for insurance depend on health status, creating simultaneity biases that could confound any causal effect of insurance coverage on health. Indeed, the only randomized evaluation of free health insurance – the RAND Health Insurance Experiment of the late 1970s – found insignificant impacts of insurance on the health status of the overall population (Newhouse et al, 1993).

An ideal study of the causal effects of health insurance would randomly assign some people to universal coverage and others to the current system. While no such experiments are in progress or currently planned, in this paper we argue that the Medicare eligibility rules create a reasonably close approximation to this ideal, with "randomization" based on whether an individual is just under or just over age 65.[4] The dramatic effects of Medicare eligibility on health insurance coverage are illustrated in Figure 1, which shows coverage rates by quarter of age from the 1992-2001 National Health Interview Surveys (NHIS). The solid line in the figure

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[1] According to tabulations of the 2002 March Current Population Survey reported in Table 1 of Mills and Bhandari (2003), 19.5 percent of people between the ages of 18 and 64 had no health insurance coverage.

[2] Recent policy initiatives for expanding health insurance coverage among lower income adults are summarized in Krebs-Carter and Holohan (2002).

[3] For example, among 50-64 year olds in the 2002 Behavioral Risk Factor Surveillance System sample, 20% of people with insurance smoke, compared with 30% of uninsured people; 75% of the insured exercise at least once per month, compared with 61% of the uninsured; 82% of the insured always wear seat belts in a car, compared to 78% of the uninsured; and 88% of the insured eat a green salad at least once a week, compared with 79% of the uninsured.

[4] Previous researchers have used the age 65 boundary to look at health related outcomes, including Lichtenberg (2001), Decker and Rapaport (2002), and McWilliams et al. (2003). Our contribution is to examine a wider variety of measures of access, utilization, and health, to quantify inter-group differences in responses to Medicare eligibility, and to focus on alternative causal channels for reaching age 65 to impact health care use and health outcomes.

represents the coverage rate for the overall population, which rises from 90 percent to 98 percent at age 65.[5] Even more striking is the impact on differences across socio-economic groups. Prior to age 65 less-educated minorities (blacks, Asians, and Hispanics with less than 12 years of education) have about 20 percent lower coverage rates than more-educated whites. After age 65 the gap narrows to 5 percentage points. If insurance coverage has a causal effect one would expect discontinuous changes in the age profiles of health outcomes at age 65, and a narrowing of inter-group disparities after age 65.

In this paper we combine information from several sources to measure the impacts of Medicare eligibility on health-related outcomes. We use survey data from the NHIS and the Behavioral Risk Factor Surveillance System (BRFSS) to examine changes in self-reported barriers to accessing care, and changes in the number of recent doctor visits, hospital stays, and frequency of diagnostic testing at age 65. We use hospital discharge records from California and Florida to examine changes in the number and characteristics of hospital admissions at age 65. We examine the age profiles of health-related behaviors (smoking, exercise) and self-reported health using NHIS and BRFSS data. Finally, we use micro data from the multiple cause of death files to study trends in death rates around age 65. Throughout the paper we focus on the differential impacts of Medicare eligibility on different subgroups, and on the question of whether these impacts arise through changes in insurance coverage or alternative channels.

As in other regression discontinuity studies, the key assumption in our research design is that measures of health care access, utilization and health status would evolve smoothly with age in the absence of the discrete change in insurance coverage at age 65. This implies that Medicare eligibility is "as good as randomly assigned" among individuals who are just a little

[5] As we discuss below, Medicare is not universal: an individual or their spouse must have a minimum of 40 quarters of work to be eligible. Medicare is also available to people under 65 in the Disability Insurance program.

older or a little younger than 65.[6] Although this assumption cannot be fully tested, it can be evaluated by checking for discontinuities in potential confounding variables like employment, income, and family structure. All the potential confounding variables we examine trend smoothly through the age 65 barrier, suggesting that any discontinuities in health-related outcomes can be attributed to Medicare eligibility.

We reach five main conclusions. First, Medicare eligibility sharply reduces disparities in access to medical care. Groups with large increases in insurance coverage at age 65 experience systematic reductions in the probability of delaying or not receiving medical care. These groups also experience increases in the probability of visiting a doctor at least once per year, and in the frequency of routine medical checkups. It is less clear whether Medicare eligibility leads to increases in specific preventative care procedures, such as blood cholesterol testing, mammography, or testing for prostate cancer, though this is partly an issue of statistical power. Second, eligibility for Medicare leads to a large (10 percent) rise in hospital stays, with the majority of the increase in non-emergency admissions and hospitalizations for elective procedures like joint replacements and bypass surgery. Contrary to an insurance-based causal explanation, however, the rise in hospitalizations is larger for whites than blacks or Hispanics, and larger for residents of areas with higher insurance coverage rates prior to age 65. Third, reaching age 65 has no systematic effect on smoking, exercise, or obesity. Fourth, Medicare eligibility appears to have small but discernable effects on the level of self-reported health, with larger gains for groups whose insurance coverage rates increased the most after becoming Medicare eligible. Fifth, we find no evidence of an immediate impact of Medicare eligibility on mortality rates at age 65, nor of a systematic change in the growth rate of mortality after 65,

[6] Lee (2003) presents a formal framework for identification in a regression discontinuity framework.

though the latter finding must be interpreted cautiously in light of the difficulty in determining mortality trends in the absence of Medicare.

I. Empirical Approach and Relation to Existing Literature

Our empirical analysis is based on a simple causal model of the effect of health insurance coverage on health outcomes:

(1) $$y_{ija} = X_{ija}\alpha_j + f_j(a) + C_{ija}\delta_j + u_{ija} ,$$

where y_{ija} is a measured outcome for individual i in group j at age a, X_{ija} represents a set of measured characteristics with group-specific coefficients (α_j), $f_j(a)$ is a smooth function representing the age profile of the outcome y (e.g., a low order polynomial), C_{ija} is a dummy variable indicating whether individual i has insurance coverage, and u_{ija} is an unobserved error component. There are a number of difficult issues underlying the specification of equation (1). One problem is that health insurance is heterogeneous (Levy and Meltzer, 2001). This is important because at age 65 many people who were previously covered by other forms of insurance switch to Medicare. Since Medicare has different reimbursement rates and coverage provisions than other insurance packages, this switch could have a causal effect even in the absence of any change in coverage. A second and related issue is that the shape of the age profile $f_j(a)$ may be influenced by the presence of Medicare. For example, 64 year-olds may delay certain medical procedures until after age 65 in anticipation of Medicare coverage.[7] Such behavior will complicate inferences based on changes from before to after 65. Third, even within groups the causal effect of health insurance may differ across people. Heterogeneity in δ_j introduces the usual problem of distinguishing between average treatment effects and the effect for those whose insurance status changes at age 65 (Angrist and Imbens, 1995).

[7] The evidence reported later in this paper shows no evidence of anticipatory behavior.

Setting these issues aside for the moment, the key problem in estimating equation (1) is that health insurance coverage is endogenous. For example, if people with pre-existing conditions cannot obtain health insurance, the error term will be correlated with coverage, leading to a positive bias in the estimated effect of coverage on health. Conversely, if healthy people are more likely to go without insurance there will be an upward bias in the estimated effect of insurance on medical care utilization and a downward bias in the estimated effect on health.[8] The age limit for Medicare eligibility at 65 provides a candidate instrumental variable for insurance coverage. As shown in Figure 1, insurance coverage rates increase sharply as individuals pass their 65th birthday, implying that the instrument has a powerful effect.

Let D_a denote an indicator for being 65 or older, and consider the following first stage model for insurance coverage:

(2) $$C_{ija} = X_{ija}\,\beta^C_j + g^C_j(a) + D_a\,\pi^C_j + v^C_{ija}\,,$$

where β^C_j is a vector of group-specific coefficients, $g^C_j(a)$ is the age profile in coverage for group j and D_a is a dummy for Medicare eligibility. Combining (1) and (2), the reduced form model for the health outcome y is

(3) $$y_{ija} = X_{ija}\,\beta^y_j + g^y_j(a) + D_a\,\pi^y_j + v^y_{ija}\,,$$

where β^y_j is a group-specific set of coefficients, $g^y_j(a)$ is a smooth age profile, and $\pi^y_j = \pi^C_j \times \delta_j$ is the reduced form effect of reaching age 65 on outcome y. The (population) instrumental variables estimate of the causal effect δ_j is just the ratio of the reduced form coefficient of D_a to the corresponding first stage coefficient:

(4) $$\delta^{IV}_j = \pi^y_j \,/\, \pi^C_j \quad .$$

[8] See Bhattacharya and Vogt (2003) for a recent survey of adverse selection issues in the health insurance market.

In our empirical analysis, we fit models like (2) and (3) to individual outcome data using OLS and probit estimators. Since the age profiles and the dummy D_a are the same for all individuals in the same age cell, however, identification of π^C_j and π^y_j comes from variation across age cells.[9] Suppressing the j subscripts for different groups, let C_a and y_a denote the population means of insurance coverage and the outcome variable in age cell a. Ignoring variation in the X's (or assuming the age cell means have been adjusted for any variation), equations (2) and (3) imply:

(2a) $C_a = k_1 + g^C(a) + D_a \pi^C$,

(3a) $y_a = k_2 + g^y(a) + D_a \pi^y$.

Standard theoretical treatments of regression discontinuity methods assume that age is measured continuously (e.g., Hahn, Todd, and van der Klaaw, 2001). Under this assumption, as long as the g( ) functions are continuous, π^C and π^y can be estimated consistently by averaging C and y in appropriate-sized windows on either side of age 65. In our data sets, however, age is measured in coarse intervals (either a quarter or a year), so the difference in means between people just over 65 and those just under 65 contains a potentially non-negligible trend component that must be estimated parametrically. An advantage of a parametric approach is that it provides some smoothing of the estimated means of the outcome data on either side of the 65 boundary.

The necessity of fitting a parametric model to the age profiles of C and y introduces an important consideration for inference. If equation (2a) or (3a) is fit to cell means with a specific functional form for the g(·) function, the error component will consist of sampling error in the

[9] It is well known that OLS estimators of the age-related parameters in models like (2) or (3) can be obtained in two stages, by first regressing the dependent variable on the X's and unrestricted age dummies, and in the second stage using the estimated age dummies as dependent variables to fit the age functions via a generalized least squares procedure.

cell mean plus any specification error.[10] Conventional standard errors obtained by estimating the discontinuity with the cell mean data incorporate both components. If the same model is estimated using the underlying micro data, however, any specification error will be ignored in the calculation of the conventional standard errors. A simple remedy is to calculate the standard errors for the micro level model allowing for a shared error component for all observations of the same age (i.e., cluster by age). This method uses the variability in mean behavior around the parametric age profile at *other* ages to estimate the sampling error of the estimated change at 65.

As illustrated in Figure 1, a key feature of Medicare is that it reduces disparities in health insurance coverage across groups. This provides the basis for a test that the impact of Medicare eligibility on a specific outcome arises through the effect on coverage, rather than through other channels. Specifically, consider a regression of π^y_j (the reduced form estimate of the effect of Medicare eligibility on outcome y for subgroup j) on π^C_j (the first stage estimate of the effect of Medicare eligibility on health insurance coverage for subgroup j):

$$(5) \qquad \pi^y_j = d_0 + d_1 \pi^C_j + e_j .$$

If Medicare eligibility only affects y through its effect on insurance coverage, and if the causal effect of insurance coverage (δ_j) is constant across groups, then $d_0 = 0$ and $d_1 = \delta$.[11] On the other hand, if the responses of outcome y to Medicare eligibility arise because of the more generous Medicare coverage, then one might expect a non-zero constant in equation (5) and a less systematic correlation between π^y_j and π^C_j. Even if Medicare eligibility only matters through

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[10] For example, let m_a denote the observed mean of outcome y for age a, and let $G(a)= k_2 + g^y(a) + D_a\pi^y$ represent the parametric model. Then $m_a=G(a) + (m_a-y_a) + (y_a-G(a))$. One source of specification error is unobserved cohort effects. In our estimation the potential for such effects is reduced by pooling several cross sections.

[11] Another way to test strict proportionality between π^C_j and π^y_j is to combine the data for different subgroups, use the interaction of D_a and dummies for the different subgroups as instruments for insurance coverage, and perform an over-identification test. In an over-identified model, the conventional IV estimator can be obtained from a generalized least squares regression of the reduced form coefficients on the first stage coefficients. The over-identification test amounts to a test that the R-squared of this regression is close enough to 1, given the sampling errors of the coefficients.

coverage, the intercept in equation (5) could be non-zero if there is significant heterogeneity in δ_j across groups that is correlated with the size of $\pi^C{}_j$.[12]

An important concern with the use of the Medicare eligibility rules to infer the causal effect of health insurance is that other factors may also change discretely at age 65. For example, 65 is a relatively common retirement age (although two thirds of men and three quarters of women have left the labor force by age 64). The potential for a variable like employment status to confound the comparison of people on either side of age 65 can be assessed by fitting a model like (2) for that variable, and testing for jumps at age 65. A specific parameterization of the age profile function g(·) is "flexible enough" if there are no significant jumps in the observed confounding variables at 65 when this age function is included in the model.

A final point worth noting is that although we estimate models like (2) and (3) using repeated cross sections of data, the models could be estimated using true longitudinal data.[13] The key advantage of longitudinal data is power: most behaviors and outcomes are strongly positively correlated over time, so changes at age 65 can be estimated more precisely with longitudinal data than with repeated cross sections. In the absence of true panel data, we compensate by pooling data from different survey years to increase our sample sizes.

[12] For example, let δ represent the mean value of δ_j , and assume that $E[\ \delta_j-\delta \mid \pi^C{}_j\ ] = \lambda\ \pi^C{}_j$. Then $E[\ \pi^y{}_j \mid \pi^C{}_j\ ] = \delta\ \pi^C{}_j\ +\ \lambda\ (\pi^C{}_j)^2$. If $\lambda>0$, $\pi^y{}_j$ is a convex function of $\pi^C{}_j$ and a linear regression will have a negative intercept, while if $\lambda< 0$ the relationship is concave and the intercept of the linear regression will be positive.

[13] McWilliams et al. (2003) use longitudinal data from the Health and Retirement Survey (HRS) to examine changes in some heath related outcomes from before to after age 65. Unfortunately, the HRS is only administered every 2 years so it is not possible to isolate changes occurring from just before to just after age 65. Kasper et al. (2000) use data from the Kaiser Survey of Family Health Experiences to look at changes in health outcomes that occur with changes in insurance status (for non-elderly adults). Neither study tries to deal with the endogeneity of insurance status.

II. Differences Among Insured and Uninsured Near-Elderly

To begin our empirical analysis, Table 1 shows some of the average characteristics of near-elderly people (ages 62-64) with and without health insurance. The data in this Table are drawn from the 1992-2001 NHIS and the 1998-2002 BRFSS. We present overall means in the first column, means for the insured and uninsured in columns 2 and 3, and simple t-tests for the difference in means by insurance status in the fourth column.

As has been shown in many other studies (e.g., Mills and Bhandari, 2003) insurance status is highly correlated with marital status, race, and education. Health care access and utilization rates also vary with insurance status. Uninsured people are more likely to report that they delayed medical care or did not get care in the past year for cost reasons (as was recently noted in Ayanian et al., 2000), and also report lower rates of use of medical services, including routine doctor visits and diagnostic exams. Interestingly, the comparisons in Table 1 show that the uninsured are *less* likely to report having been diagnosed with hypertension or heart-related problems than people with insurance. This could reflect the fact that insurance is more valuable for people with known health problems, or lack of awareness of latent conditions among the uninsured. Despite lower reported rates of hypertension and heart problems, the uninsured have lower self-assessed health, a pattern that is potentially supportive of an awareness explanation.

Some of the observed health differences between the insured and uninsured groups in Table 1 are arguably a result of the different compositions of the two populations. Table 2 presents comparisons of some key outcomes by insurance status for four narrowly defined subgroups, based on education (high school diploma or not) and ethnicity (white non-Hispanic or not). For example, columns 2 and 3 of Table 2 compare the fractions of insured and uninsured people in different subgroups who reported that they delayed receiving health care last year for cost reasons. The rates for insured and uninsured people in the four subgroups are quite similar, suggesting that insurance status is more important than education or ethnicity in explaining reported delays in health care. A similar pattern holds for the probability of seeing a doctor at least once in the past year (columns 5 and 6). Doctor visit rates for the insured fall in a narrow range around 85 percent while rates for the uninsured center around 65 percent. For the other outcomes in Table 2, however, incidence rates vary more across subgroups even holding constant insurance status. For example, the probability of a hospital stay in the past year ranges from 10 to 15 percent among insured people in different race/education groups, and from 5 to 9 percent among uninsured people. Mammography and cholesterol testing rates also vary substantially by education, holding constant insurance status.

III. Changes in Insurance Coverage at Age 65

Medicare is available to people who are at least 65 years of age and who worked at least 40 quarters in covered employment (or have a spouse who qualifies for coverage).[14] For those whose meet the eligibility criteria, Medicare hospital insurance (Part A) is available free of charge and Medicare Part B (Medicare insurance) is available for a modest monthly premium. Normally, individuals who are approaching their 65th birthday receive notice of impending eligibility and are informed that they have to enroll in the program and choose whether or not to accept Medicare Part B coverage.

Table 3 presents estimates of the effect of reaching the Medicare eligibility age on insurance coverage, based on alternative specifications of equation (2) fit to data from the 1992-

[14]Medicare is also available to people under 65 who are receiving Disability Insurance, and those with kidney disease. Individuals who do not qualify on the basis of their own or their spouse's work history may still enroll in Medicare at age 65 by paying monthly premiums for both Part A and Part B coverage. This option is limited to U.S. citizens and legal aliens with at least five years of residency in the U.S.

2001 NHIS.[15] In all cases the age profile function ($g^C(a)$) is assumed to be quadratic with coefficients that are allowed to differ for those older or younger than 65. This functional form assumes that the age profile is continuous at age 65, but allows both the first and second derivatives to jump discretely at 65. We report estimates for the entire sample in the top row, and for four ethnicity/education categories, three ethnicity groups, and for men and women.

The models in the first column of Table 3 are fit to mean coverage rates by quarter of age. As suggested by the patterns in Figure 1, the jumps in coverage at age 65 are precisely estimated, reflecting the smoothness of the coverage profiles before and after 65 and the sharpness of the rise at 65. The gain in coverage for the overall population is estimated to be 8.4 percentage points, while the gains by ethnicity/education group range from 5.3 to 18.8 percentage points. Interestingly, the estimated gain is about one third larger for women than men.

Column 2 reports estimates of the same specifications, fit by linear probability model to the underlying micro data. Since we used a weighted estimation procedure for the cell-level models the coefficient estimates are identical in columns 1 and 2.[16] As expected, however, the standard errors are slightly different. The standard errors in column 2 are calculated allowing heteroskedasticity and an unrestricted correlation structure for observations from the same age cell. These are larger than the conventional standard errors for the same micro models (which ignore clustering by age), but about the same size as the standard errors from the cell level models. Column 3 presents models in which we add a set of micro-level control variables, including dummies for the survey year and for gender, ethnicity, education and region. Although

[15] We construct age in our NHIS samples from data on year and month of birth and quarter of the interview, as well as age (reported in years). The latter information allows us to precisely separate people on either side of their 65th birthday. We restrict the samples to people between 55.25 and 74.75 (79 quarters).

[16] Specifically, we weight the cell-level observations by the sum of the sampling weights for the people in each cell. The micro models are weighted, using the individual sampling weights.

the covariates are highly significant, they vary smoothly with age, and the point estimates of the rise in coverage at age 65 are hardly affected. Finally, in column 4 we fit the micro level models using a probit procedure to account for the dichotomous nature of the dependent variable. The table reports derivatives of the predicted probabilities of coverage, evaluated at the mean predicted probability. These are uniformly smaller than estimated jumps in coverage from the linear probability models, but provide a qualitatively similar picture.

We have experimented with a number of alternative specifications and sample choices for estimating the effects of reaching age 65 on insurance coverage. Appendix Table 1 reports results from models like those in Table 3 fit to the last 5 years of the NHIS data (1997-2001) and to the 1998-2002 BRFSS sample.[17] The results are qualitatively and quantitatively similar to the results in Table 3. We have also examined different specifications of the age profiles. For example, in some specifications we included a cubic or quartic of age rather than the quadratic interacted with the post-65 dummy. The sizes of the estimated jumps in coverage at age 65 are robust to all the alternatives we have tried.

Examining changes in the probability of *any* health insurance coverage at age 65 ignores potential changes in the composition of insurance coverage. Immediately upon reaching age 65, many people drop (or lose) private insurance coverage, while others obtain multiple coverage. Figure 2 shows the age profiles of Medicare coverage for the same groups as in Figure 1, while column 5 of Table 3 reports estimates of the rise in Medicare coverage at 65 (based on a linear probability model identical to the specification in column 3). Medicare coverage rates are low but rising before age 65, reflecting the movement of non-elderly disabled people onto the Social

[17] In the BRFSS individuals are asked their current age but not their date of birth, so we use age in years rather than quarters. To increase the number of age cells, we use data from ages 50-80. We also used March Current Population Survey data to look at the age profile of insurance coverage. Results are qualitatively similar, although insurance coverage rates are a little different in the CPS, reflecting in part the wording of the coverage question, which refers to coverage at any time in the previous calendar year.

Security Disability Insurance (DI) program. As noted elsewhere (e.g. Autor and Duggan, 2003), DI participation is particularly high for less-educated minorities, reaching 20 percent by age 64. Immediately after age 65, average Medicare participation rates rise to around 85 percent, with higher rates for highly educated whites and lower rates for less-educated blacks and Hispanics.[18] The reversal of Medicare participation rankings across education/ethnicity groups at age 65 means that the groups with bigger gains in net insurance coverage at age 65 have smaller rises in Medicare coverage.

To what extent do changes in health insurance coverage at 65 coincide with other discrete changes? An obvious confounder is employment. Historically, many public and private pensions became available at 65, and 65 was widely imposed as a mandatory retirement age.[19] Figure 3 shows the age profile of employment for men, along with the corresponding profile of insurance coverage.[20] Unlike insurance coverage, employment rates decline smoothly from age 55 onward, with no evidence of a discontinuous shift at age 65. The first column of Appendix Table 2 reports estimation results for a set of employment models similar to the specifications in column 3 of Table 3, based on pooled 1992-2001 NHIS data. The estimated jumps in employment at age 65 are generally small in magnitude and statistically insignificant, with the exception of a positive and significant rise for less educated minorities. Similar models fit to cell level data on current employment status from the pooled 1996-2002 March Current Population Surveys, reported in the second column of the table, also yield estimated jumps at 65 that are small in magnitude and mostly statistically insignificant. Interestingly, the estimated jump in

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[18] Incomplete coverage of people over 65 reflects a number of factors, including the minimum work history requirements for Medicare and under-reporting.

[19] See von Wachter (2002) for an analysis of retirement rates and the impact of changes in laws governing compulsory retirement. Over the past two decades 62 has replaced 65 as the most common retirement age.

[20] The corresponding figure for women shows the same smooth decline in employment though women start with significantly lower employment rates at age 55 than men.

employment for less educated minorities in the CPS data is negative, suggesting that the positive estimate in NHIS data is spurious. We conclude that employment changes are relatively smooth at age 65, and are unlikely to drive changes in health-related outcomes around age 65.

We have also investigated the age profiles of marriage, family income, and residential mobility using the 1996-2002 CPS data. Columns 3-6 of Appendix Table 2 show the estimated jumps at age 65 in the fraction of people who are married and living with their spouse, the fractions whose annual family income is under $10,000, under $15,000, and under $20,000, and the fraction who changed houses in the past year.[21] For the overall sample and for the four education/ethnicity subgroups, none of these outcomes shows a large or statistically significant change at age 65. These results suggest that family structure, family location, and family income all evolve smoothly around age 65, and are unlikely to confound our analysis of the impact of Medicare eligibility.

IV. Changes in Health Care Access and Utilization at Age 65

a. Measures of Access

We now turn to an analysis of the effects of reaching age 65 on access to and utilization of health care services. We begin with self-reported measures of access. Starting in 1997, the NHIS asked two questions of all adults in the survey: (1) "during the past 12 months has medical care been delayed for this person because of worry about the cost?" (2) "during the past 12 months was there any time when this person needed medical care but did not get it because (this person) could not afford it?" Recent waves of the BRFSS have asked a closely related question: "Was there a time during the past 12 months when you needed to see a doctor but could not

[21] We do not report results on the poverty rate (or on income relative to the poverty line) because the poverty line changes discretely at age 65. For example, the poverty line for a single individual is reduced by 8% when the person reaches 65. As one would expect, graphs of poverty rates by age show a small jump down at 65. The samples include individuals aged 50-79.

because of the cost?" Figure 4 shows the age profiles of responses to the first question in the NHIS, while Figures 5a and 5b show the age profiles of responses the second question in the NHIS and the similar question in the BRFSS. Consistent with the hypothesis that having medical insurance increases access to medical care, all three graphs show a sharp drop in the fraction of less-educated minorities who report delaying or not getting care after age 65.

The first three columns of Table 4 show the estimated changes in the probability of delaying or not receiving medical care at age 65, based on linear probability models similar to those in column 3 of Table 3. As suggested by the patterns in Figures 4 and 5, all three access measures show significant decreases at age 65 among less educated minorities. There is also reasonably strong evidence of a discrete change in access for all blacks and all Hispanics. The estimated jumps in column 3 (based on the BRFSS question) are larger than the estimates in column 2 (based on the similar question in the NHIS), and suggest very systematic impacts of insurance coverage on medical care access. The ratio of the coefficients in column 3 to those in column 3 of Table 3 ranges from -0.2 to -0.6, with most of the implied IV estimates of the effect of insurance on the probability of not receiving care in the range of -0.3 to -0.4.[22] Corresponding estimates based on the NHIS version of the question imply smaller effects, ranging from 0 to -0.3. Given the apparent sensitivity of responses to the question based on wording and placement in the survey, the magnitude of the effects from the BRFSS should probably be viewed cautiously. Nevertheless, it seems clear that the incidence of cost-related access problems falls sharply at age 65 among the groups with the largest gains in insurance coverage.[23]

[22] The impacts of reaching age 65 on insurance coverage using the BRFSS data tend to be a little larger than those in Table 3 (see Appendix Table 2), implying slightly smaller IV estimates.

[23] Because the questions on access refer to the previous year, our estimates of the effect of reaching 65 on access problems are potentially attenuated. Specifically, someone who turned 65 less than a year ago could have had problems in the months before his or her birthday. The attenuation may be mitigated by recall errors and the saliency of the recent past.

Another measure of access to the health care system is whether an individual has a usual place for routine preventative care. Since the late 1990s the NHIS has included a sequence of questions that can be used to construct such a measure.[24] As shown in column 4 of Table 4, there is some indication that the probability of having a usual place for routine preventative care rises at age 65, especially for black non-Hispanics. Unlike the measures of delaying or not receiving care, however, this measure shows only a small effect for less educated minorities.

b. Doctor Visits and Hospitalization

The right hand columns of Table 4 present estimation results for two key measures of health care utilization: did the individual have at least one doctor visit in the past year? Did the individual have one or more overnight hospital stays in the past year? (Both measures are taken from the 1992-2001 NHIS). Since these questions refer to flows over the past year, they will not necessarily respond instantaneously to changes in insurance coverage. To the extent that uninsured people are delaying or not getting care, however, one might expect discrete changes at age 65 as Medicare becomes available.

Figure 6 shows the age profiles for the fraction of people with at least one doctor visit in the previous year. A close look at the graph suggests that the gap in frequency of doctor visits between less educated minorities and other groups closes between ages 65 and 66, although the age profiles are noisy. The estimates in column 5 of Table 4 confirm that less educated whites, less educated minorities, and non-Hispanic blacks all show significant or nearly significant rises in the probability of visiting a doctor after age 65. These patterns are consistent with the estimates for the access measures in columns 1-3.

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[24] The survey first asks if a person has a place they usually go when sick, and if yes, whether they also get routine preventative care there, or somewhere else. For those who do not identify a place they usually go when sick, a third question asks if they have a place they usually go for routine preventative care. These questions are only asked of the "sample adult" in each household.

Figure 7 shows the age profiles of the incidence of an overnight hospital stay. There is a discernable jump in the hospitalization rate of the overall population, but unlike the patterns in many of the previous graphs there is no indication that the rise is bigger for less educated minorities. Consistent with this conclusion, the estimated changes in the probability of a hospital stay in column 6 of Table 4 are fairly stable across groups. The point estimates center around 1-2 percentage points – a relatively large effect, considering that the probability of a hospital stay in the previous year for 64 year olds is around 12 percent. In the next section we use very large samples of hospital discharge records to refine these estimates. As in the models in column 6, the discharge data suggest that increases in hospitalization at 65 are if anything smaller for subgroups with the larger net gains in insurance coverage.

c. Screening and Preventative Care

One concern often raised about lack of health insurance coverage is that the uninsured will not get preventative care, leading to long term health problems that could have been avoided by earlier diagnosis and prophylactic treatment (e.g., Powell-Griner et al., 1999). Table 5 presents estimates of the impact of reaching age 65 on several measures of preventative care, including influenza vaccination, blood cholesterol screening, mammography, and screening for prostate cancer. All these models are estimated using data from the 1999-2002 BRFSS.[25] As with doctor visits and hospitalization, one issue with outcomes like mammography or prostate screening is that people may not respond instantaneously to the availability of insurance. To partially address this concern, we include models for whether an individual has *ever had* a mammogram or either a digital rectal exam or prostate-specific antigen (PSA) test. The final

[25] A major problem with the BRFSS is that not all questions are asked in all states in all years. For example, the flu shot question was only asked in a minority of states in 2000, cholesterol testing was only asked in most states in 1999 and 2001, and the prostate screening questions were only asked in most states in 2001 and 2002.

column of Table 5 also reports a model for the probability of ever having been diagnosed with hypertension.

Column 1 reports models for having a flu shot in the past year. Only the age profile of less educated whites shows a significant jump at 65, though the standard errors for all groups are relatively large.[26] The models for recent cholesterol testing in column 2 also show a large jump for less-educated whites at age 65, and relatively modest changes for other groups.[27] The models for the probability of having a mammogram in the past two years yield relatively imprecise estimates, but point toward a large gain for less educated minorities. The age profiles for this outcome are shown in Figure 8. The profile for less educated minorities rises at age 65, but the variability of the profile at earlier and later ages suggests the need for caution in inferring too much from the point estimates in Table 5. Although for space reasons we have not included a graph of the age profiles for the probability of ever having a mammogram, these are flat by age 50, suggesting that there are very few women who have their first mammogram after reaching middle age. As shown by the estimates in column 4 of Table 5 there is no indication of an upward jump after age 65 for any of the subgroups. In fact, the probability of ever having a mammogram among Hispanic women is estimated to drop down. Since the true response cannot decline, we attribute this estimate to an unlucky combination of sampling errors.

We have also fit a series of models for the probability of a clinical breast examination in the past two years, and the probability of a pap smear test in the past two years. None of the

[26] Overall, the rate of flu shots for 64 year olds is about 50 percent, with variation across ethnic and education groups that follows the expected pattern. The fraction of people who have a shot is strongly increasing with age for groups. The 5 point rise for less-educated whites is readily discernable in a graph. The increase in flu shots should be interpreted with caution given that the CDC's list of groups at risk of flu related complications includes adults age 65 or older.

[27] About 82 percent of 64 year olds report having had a cholesterol test in the past two years. The rate for better educated whites is about 86 percent while the rate for less educated whites and less educated minorities is 72 percent.

estimated jumps at age 65 for the various subgroups are statistically significant for either outcome, although this is partly a reflection of relatively large sampling errors – in the range of 1-2 percent for most subgroups, and about 3 percent for less educated minorities. Thus, we cannot rule out effect sizes as large as 4-5 percent in most cases.

Columns 5 and 6 refer to the incidence of tests for prostate cancer. We decided to combine the two tests (the traditional digital rectal exam and the more recent prostate specific antigen blood test) to focus on the possibility that older men had neither test.[28] Unfortunately, the sampling errors for this outcome are relatively large, reflecting the fact that the questions were only asked in most states in the two most recent years of our BRFSS sample. The results in column 5 suggest an impact of reaching age 65 on screening rates among Hispanics but not for blacks, leading to mixed results in the two minority/education categories. The results for the ever tested measure in column 6 are all insignificant and more narrowly centered around 0.

A final preventative care outcome considered in Table 5 is the probability of ever being diagnosed with hypertension. Untreated high blood pressure is an important health risk, especially among minorities (Hyman and Pavlik, 2001), although lack of treatment does not necessarily arise because people are unaware of their condition. Nevertheless, the estimates in the final column of the table (which are based on the subset of "sample adults" in the 1997-2001 NHIS) suggest that there is a sizeable increase in the fraction of minorities of both higher and lower educational attainment who are diagnosed with hypertension at age 65.[29] A graph reveals that although the age profiles for the two minority groups are noisy, they seem to jump after age

[28] The Food and Drug Administration approved the PSA test in conjunction with a digital rectal exam to help detect cancer (National Cancer Institute, 2001). In the data, most men report receiving both tests or neither.
[29] Overall, about 45 percent of 64 year olds report having been diagnosed with hypertension at some point. The rate is around 42 percent for more educated whites, and 60 percent for less educated minorities.

65. As with the other preventative care measures in Table 5, however, the underlying sample sizes are not large enough to permit precise inferences.

Our reading of the results in Table 5 is that they lend support to the hypothesis that Medicare eligibility at age 65 leads to modest increases in the incidence of preventative screening, and that the increase is concentrated among groups with a larger rise in net insurance coverage. Unfortunately, our main data source for preventative screening – the BRFSS – did not ask screening questions in all states in all years. Moreover, breast cancer and prostate cancer are gender-specific so the sample sizes for these outcomes are cut in half. Because of these data limitations, and the fact that people may not seek screening immediately after getting insurance, the power of our discontinuity-based research design is limited, and we cannot reach definitive conclusions.

V. Changes in Hospitalization - Evidence from Discharge Data

Survey data from the NHIS and BRFSS suggest that reaching age 65 has a significant effect on the extent and composition of insurance coverage, on self-reported access to care, and on utilization of medical services. In particular, data from the NHIS show a surprisingly large increase in hospitalization rates at age 65, fairly evenly distributed across subgroups. In this section we use data from the hospital discharge records for the states of California and Florida to examine changes in the number and characteristics of hospital admissions by age. These administrative data sets are very large and provide detailed information on the reasons for admission to the hospital, the procedures performed, and the cost and duration of the hospital stay. Their main disadvantage is the absence of information on a patient's education (a key determinant of pre-65 insurance coverage) and the fact that we only see people who enter the hospital. For comparison with the state data, we also make use of national samples from the

National Hospital Discharge Survey. While these data have the advantage of being drawn from a nationally representative survey, they have a limited set of covariates and smaller sample sizes.

Our approach to the problem of only observing those who enter the hospital is to assume that the underlying population at risk for hospitalization varies smoothly with age. Specifically, consider a simple reduced form model for p_{ja}, the probability that an individual of age a in subgroup j is admitted to the hospital in a given time interval:

$$(6) \qquad \log (p_{ja}) = g^p{}_j(a) + D_a \pi^p{}_j + v^p{}_{ja} ,$$

where $g^p{}_j(a)$ is a smooth age profile, D_a is a dummy for age 65 or older, and $v^p{}_{ja}$ is a specification error component. Let N_{ja} represent the population in subgroup j of age a and let A_{ja} represent the number who are admitted to hospital, so the ratio A_{ja}/N_{ja} is an estimate of p_{ja}. Finally, assume that the log of the population in group j at different ages follows a smooth trend:

$$(7) \qquad \log (N_{ja}) = h_j(a) .$$

Equations (6) and (7) imply that the log of the number of hospital admissions in subgroup j at age a is given by:

$$(8) \qquad \log (A_{ja}) = [g^p{}_j(a) + h_j(a)] + D_a \pi^p{}_j + v^p{}_{ja} + \varepsilon_{ja} ,$$

where

$$\varepsilon_{ja} = \log (A_{ja}/N_{ja}) - \log (p_{ja})$$

represents sampling error in the observed admission ratio. Provided that the underlying population varies smoothly by age, any discontinuity in hospital admissions at age 65 can be attributed to a corresponding discontinuity in the log of the probability of admission.

Our state-level hospital discharge data files consist of 100% of individuals who were admitted to hospitals in California or Florida and discharged between January 1st 1995 and December 31st 1999 (in the case of California) or between January 1st 1995 and December 31st

2000 (in the case of Florida).[30] We focus on individuals between the ages of 50 and 75 at the time of their admission, yielding samples of 4,069,049 discharges in California and 3,550,784 in Florida. In the national data, we pool discharges for individuals in the same age range during 1995-1999, and obtain a sample of 413,866 observations.

Figure 9 shows the age profiles of the overall number of admissions in California and Florida. To make it easier to compare the two states, we have normalized each series by the log of the average number of discharges among 60-64 year olds. In both states there is clear evidence of a discontinuous increase in hospital admissions at age 65, equivalent to about a 5-10 percent rise. Interestingly, the rise seems to be "permanent" – the state-specific age trend in admissions is about the same between ages 65 and 70 as between ages 60 and 64. The lack of any relative decline from 65 to 66 suggests that the jump at 65 is primarily the result of new admission criteria being applied once potential admittees become Medicare-eligible, rather than to a "catch-up" for care that had been deferred prior to age 65.

Figure 10 shows the age profiles in admissions for three major ethnic groups (white non-Hispanics, black non-Hispanics, and Hispanics) in the two states. In both states whites experience the largest proportional increases in hospital admissions, with slightly smaller rises for Hispanics and virtually no rise for blacks. These patterns are potentially surprising, considering that the rise in net insurance coverage at age 65 is largest for Hispanics, smallest for whites, and in the middle for blacks.[31]

The upper panel of Table 6 shows estimates of the jump in log hospital admissions at age 65, based on a specification of equation (8) that includes a quadratic in age, fully interacted with

[30] The data sets exclude Veteran Administration hospitals. For our analysis, we focus on patients admitted from home.

[31] We used the BRFSS data set (which has state identifiers) to estimate the rises in insurance coverage at age 65 for people in California and Florida only. Overall, the rise is a little bigger in Florida (13 points) than California (10 points). Within either state, however, the patterns by ethnic group are very close to those reported in Table 3.

a dummy for age 65 or older. We also show estimates of jumps in three characteristics of the hospital stays at each age: the mean duration of the stay (in days), the average amount charged by the hospital for the stay, and the fraction of admittees who died in the hospital. Looking first at the models for the number of admissions (columns 1, 5, and 9), we estimate that the number of admissions rises by 6.0 percent at age 65 in California, 11.4 percent in Florida, and by 6.4 percent nationwide. Across the three major ethnic groups, the rise is largest for white non-Hispanics, a little smaller for Hispanics, and negligible for black non-Hispanics. The sampling errors are small enough that in both states we can reject the hypothesis that the rise in admissions is the same for blacks as the other two groups, although the rises for whites and Hispanics are insignificantly different.

The results for length of stay and in-hospital mortality suggest that the hospital caseload becomes less sick at age 65, consistent with the notion that the extra admittees after 65 are relatively healthy. As we show below, this is consistent with bigger increases at age 65 in non-life-threatening diagnoses. The patterns in the changes in duration and mortality by ethnic group are also generally consistent with this hypothesis. Interestingly, average hospital charges do not change much in California but show a decline in Florida.

The lower panel of Table 6 shows estimates of the number and characteristics of hospital stays, classified by route into the hospital (emergency room or not), and by whether the admission was for elective, urgent, or emergency care (which is only coded in the Florida data). In California, almost all the discontinuous growth in admissions at age 65 is driven by non-emergency room admissions. In Florida, there is some increase in both emergency room and non-ER admissions, but the percentage increase in non-ER admissions is nearly three times bigger. When the data are classified by type of admission, the patterns reinforce the conclusion that most of the rise in hospitalization at age 65 is attributable to an increase in discretionary medical care: the rise in elective care admissions is 19.1 percent versus 5.6 percent for emergency care admissions.

As noted, the discharge files have no information on education, which is a key predictor of insurance coverage status prior to age 65. As an alternative, we used geographic information in the Florida files to estimate the fraction of 50-64 year old admittees who were uninsured by zip code of residence. (This is estimated as the fraction of all dischargees who paid their own bill, or were classified as indigent or charity care cases). We then divided all zip codes in the state into four equally-sized groups, ranked by the fraction of 50-64 year olds without insurance. Figure 11 shows the age profiles in the number of admissions from the four zip code groups, while Table 7 shows estimates of the jumps at age 65 in the number and characteristics of admissions by group. Contrary to the view that the rise in admissions at age 65 is driven by new inflows of people who previously lacked coverage, the jump in admissions is largest for residents of areas with highest rates of insurance before age 65, and smallest for residents of areas with the lowest rates of insurance prior to 65 (though the difference in the jump at 65 is not statistically significant). The shifts in duration of stay is somewhat imprecisely estimated and not much different across the four zip code areas, while changes in in-hospital mortality rates are only observed for the two “low insurance” groups.

As a final step in analyzing the discharge files, we tabulated the most common ICD-9 codes assigned as reasons for admission among people ages 60-64, and the most common primary procedures performed during the hospital stay. Figure 12 shows the age profiles for 6 of the most common admission diagnoses in California: chronic ischemic heart disease (IHD, often treated by bypass surgery), acute myocardial infarction (AMI or heart attack), heart failure, chronic bronchitis, osteoarthrosis (degenerative joint disease, often treated by joint replacement), and pneumonia. The figure reveals large discontinuous increases in admissions at age 65 for IHD and osteoarthrosis, smaller increases for AMI, chronic bronchitis and pneumonia and no increase for heart failure. The estimation results in the upper panel of Table 8 confirm these impressions, revealing relatively large jumps at age 65 in admissions for IHD and osteoarthrosis in both California and Florida, and much smaller jumps for AMI and pneumonia. The national estimates are roughly consistent with the state data, but are much less precisely estimated due to the smaller samples. The rises in admission for AMI are potentially surprising, and suggest that a significant number of people under 65 who have heart attacks are either not treated or are treated on an outpatient basis.[32]

The results by type of procedure in the lower panel of Table 8 confirm the importance of discrete rises in admissions related to joint replacement surgery and heart bypass surgery at age 65. Rises in the number of discharges with joint replacements of the lower extremity (hip and knee replacements) parallel to the rises in admission for osteoarthrosis diagnoses. Similarly, rises in removal of coronary artery obstruction and bypass anastomosis are comparable to the rise in admissions for IHD diagnoses. Finally, it is interesting to note that the increase in admissions for people who receive no procedures is below the overall growth in admissions in both states (4.7% versus an overall average of 6.0% in California, 9.2% versus an overall average of 11.4% in Florida), but is above the overall growth in admissions nationwide (8.5% versus an overall average of 6.4%).

[32] Another possibility is that once people become eligible for Medicare, hospitals assign different diagnoses codes for certain symptoms to increase their billings. Some of this may arise because of a shift in caseloads across hospitals at age 65. In particular, people over 65 are more likely to be admitted to private hospitals and less likely to be admitted to county hospitals.

Taken as a whole, the results from our analysis of hospital discharge records suggest that although reaching age 65 has an important effect on utilization of inpatient hospital services, the patterns by ethnicity, region, type of admission, and procedure all point to a causal mechanism *other than* insurance coverage per se. The relatively larger increases in hospitalization after age 65 for white non-Hispanics and residents of areas with the highest rates of insurance coverage among 50-64 year olds, and the very large rises for bypass surgery and joint replacement at 65, suggest to us that the changes are driven by features of the Medicare system, such as relatively generous coverage of hospital services, rather than to the fact that coverage rises at the Medicare age limit. The effect may be more pronounced among relatively wealthy Medicare recipients because they can afford the out-of-pocket costs of surgery or have secondary insurance (Medigap or retiree health insurance) that reduces those costs.

Interestingly, a recent panel of the National Institute of Health concluded that hip and knee replacement surgeries contribute significantly to quality of life and are *under-performed* in the U.S. If true, this implies that the rise in admissions for these procedures at age 65 may be due to excessively stringent limitations in the insurance coverage available prior to age 65, rather than to overly generous Medicare reimbursement rates for these procedures.

VI. Changes in Health-Related Behaviors

As we noted in Table 1, insured and uninsured people differ in several important health related behaviors, including smoking, diet, and exercise. In Table 9, we investigate whether there are any discrete changes in the age profiles of smoking, exercise, and weight outcomes at age 65, using data from the 1999-2002 BRFSS.[33] Increased access to routine medical care after

[33] The smoking measure we use is whether an individual smokes daily. Results for smoking at all are very similar. The exercise measure is "During the past month, did you participate in any physical activities or exercises such as running, calisthenics, golf, gardening or walking for exercise?"

age 65 may increase awareness of the health consequences of smoking, exercise, and weight, causing some people to change their behavior and creating a pathway for Medicare eligibility to affect health.

The age profiles for the probabilities of smoking, participating in exercise, and of being overweight (body mass index in excess of 25) or obese (body mass index in excess of 30) all follow relatively smooth downward trends between the ages of 50 and 80. The estimates in Table 9 show that there are no large or statistically significant jumps in smoking or exercise participation. There is some indication, however, of a rise in the probability of being overweight or obese for less educated minorities and for blacks. These rises are noticeable in a graph, but appear to be driven by a downward dip among 63 and 64 year olds, rather than a systematic rise at age 65. We therefore attribute the point estimates to misspecification of the age profiles and/or sampling error, rather than to Medicare eligibility.

Overall, we conclude that health behaviors evolve smoothly with age, and do not change suddenly at 65. In view of the extensive literature on habit persistence in smoking, eating, and other lifestyle choices this is perhaps unsurprising. The implication is that health related behaviors are unlikely to be an important channel through which Medicare eligibility affects health or mortality at age 65.

VII. Changes in Self-Reported Health

In this section, we turn to an analysis of trends in self-reported health before and after age 65. At the outset it should be noted that even if Medicare eligibility leads to increased use of medical services, it is unclear how this will affect the age profiles of self-assessed health. One possibility is that more preventative care and diagnostic testing leads to a shift in the *rate of* *change* of true health status that translates to a shift in the rate of change of subjective health.[34] Such a phenomenon can only be measured under stronger assumptions than the smoothness assumptions underlying equations (2) and (3). In particular, identification of a causal effect on the derivative of health requires an assumption that the age profile of health of uninsured people has continuous first derivatives.[35] An alternative possibility is that improved access to care after age 65 leads to a discrete shift in self-assessed health. The shift could be positive (if certain health problems can be resolved quickly, or if uncertainty about a chronic condition can be resolved) or negative (if there is a "labeling effect" as people are informed about previously unrecognized conditions, or if treatment causes serious side effects).

Both the NHIS and the BRFSS ask individuals to give an assessment of their own health on a 5-point scale: excellent, very good, good, fair, or poor.[36] Figure 13 shows the age profiles of the fraction of the population who report themselves to be in good, very good, or excellent health, based on pooled 1992-2001 NHIS samples. Inspection of the graphs shows that health is generally declining with age. The rate of decline before age 65 for less educated minorities is a little faster than for the overall population, implying that the SES gradient in health is widening with age (Case and Deaton, 2003). Some time in the mid-60s the profile for less educated minorities gradually flattens, and between 65 and 75 there is some convergence in health between less educated minorities and the overall population. While this is consistent with a causal effect of insurance coverage on the rate of change of health, it is clearly impossible to

[34] Baker et al. (2001) analyzed data from the Health and Retirement Survey and concluded that lack of insurance contributed to an increased risk of health declines among 51-61 year olds.

[35] More precisely, consider two assumptions: (i) equation (1) includes an interaction between age and coverage status $\lambda_j(a)\times C_{ija}$; (ii) the age functions $f_j(a)$ in the structural outcome equation and $g^C{}_j(a)$ in the first stage coverage equation have continuous first derivatives. In this case the reduced form outcome equation includes a term like $\lambda_j(a)D_a$ (an interaction of an age function with the dummy for age 65 or older), and any discrete change in the first derivative of the reduced form profile at age 65 is interpretable as a causal effect of coverage.

[36] There is an extensive literature on the reliability and interpretation of self-reported health, including Bound (1991), Waidman et al. (1995), and Crossley and Kennedy (2002).

pinpoint the precise turning point in the rate of change of health of less educated minorities. Given the quarter-to-quarter variability in the age profiles, it is also hard to discern whether there is a discrete shift in the level of self-assessed health at 65. Similar features are evident in a graph of the age profiles of the assessment of health (assigning 1 to poor health and 5 to excellent).

Table 10 presents a series of estimates of the jump in self-assessed health at age 65. The first column presents estimates from linear probability models for the event that people report their health as good or better. The second and third columns presents estimates from models for the mean assessment of health (rated 1 to 5): column 2 reports estimates from a simple linear regression, while column 3 presents estimates from an ordered probit model.[37] Although the estimates are somewhat imprecise, the pattern across subgroups is similar across specifications and consistent with a causal link from insurance coverage to self-assessed health. For example, the jumps are relatively large for less educated minorities and Hispanics and relatively small for whites and better educated subgroups. The estimated effects from the ordered probit model, for example, suggest that the mean assessment of less educated minorities and Hispanics increases by about one-tenth of a category at age 65 – equivalent to closing about 15% of the gap in mean assessments between the overall population and either subgroup.

VIII. Trends in Mortality

In this section, we analyze trends in mortality before and after age 65. The previous sections have documented that Medicare eligibility leads to significant increases in access to and use of medical services. This could change the probability of dying in two ways. For acute, life threatening conditions, it is possible that improved access to hospital care reduces the probability of dying immediately after becoming eligible for Medicare at age 65. For non-acute conditions,

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[37] The estimates in columns 2 and 3 are multiplied by 100. A coefficient of 10 implies that the mean assessment rises by .1 (or one tenth of a category).

improved access to care might increase the life expectancy of individuals who would not have died immediately in the absence of Medicare.

We begin by testing for a discrete change in mortality rates at age 65 using a regression discontinuity design. We then tackle the more complicated problem of testing for less immediate changes in mortality rates resulting from Medicare coverage. We implement two approaches to estimating the long-term effects of Medicare coverage. First, we compare projected mortality rates among 66 and 67 year olds with the actual rates. Second, we look for comparison groups not exposed to Medicare whose mortality rates may serve as a plausible counterfactual. In our first comparison, we consider mortality rates in the five years before and after Medicare was implemented in 1966.[38] The second comparison we make is between Canada and the United States during the time period 1990-1995. While informative, these two comparisons suffer from several limitations that are detailed below.

To test for the possibility of a discrete reduction in mortality at age 65, we construct age-specific death rates by gender, race and ethnicity.[39] In the numerator, we use the number of deaths at each age listed in the Multiple Cause of Death file from the US Department of Health Services National Center for Health Statistics. In the denominator, we use postcensal estimates of the mid-year resident population of the United States by single year of age. Although the denominator is a simple characterization of the population's exposure to the risk of dying (i.e., period person-years lived), we have experimented with more sophisticated estimates of exposure based on different assumptions about the timing of deaths and found these to make little

[38] Although Medicare was enacted on July 30, 1965, it was not implemented until July 1, 1966.

[39] We depart from our earlier approach of looking at race-education groups. Although educational attainment has been reported on the death certificate since 1989, there is evidence of severe misreporting of education, especially at older ages (Sorlie, 1996).

difference. In order to get more precise estimates, we pool deaths over the period 1989-1998 and sum mid-year population estimates over the same period.

In Figure 14, we plot the age profiles of death rates by gender and race/ethnicity. There is no evidence of a discontinuous change in mortality at age 65 for any of the six subgroups. In the first row of Table 11 we present the corresponding regression discontinuity estimates, based on a specification that includes a cubic polynomial in age, fully interacted with an age 65 dummy. Consistent with the patterns in Figure 14, there is no evidence of a shift in mortality at age 65 for any of the groups. All of the point estimates are insignificant and all but one are positive -- the opposite of what would be expected if insurance coverage causes an instantaneous reduction in mortality.[40]

For most conditions, if Medicare has an impact on 65 year olds, it will increase the life expectancy of those not at immediate risk of dying. This is much harder to detect than an immediate, discrete change in mortality because death rates will change slowly over time as deaths are shifted from earlier to later ages throughout the age distribution. We begin by examining the possibility that Medicare may slow the rate of increase in mortality rates by comparing the actual mortality rates among 66 and 67 year olds with those predicted by fitting a cubic polynomial to the mortality rates of 50 to 64 year olds. The actual and predicted mortality experience of 66 year olds is presented in rows 3 and 4 of Table 11. For all but one sub sample, the actual mortality rate of 66 year olds is slightly higher than the predicted rate (consistent with small but positive estimates of the jump in mortality rates at age 65). As can be seen in the bottom two rows of the table, the same is true for 67 year olds, though the gap between actual

[40] We ran similar regression for the 6 most common causes of death and found no evidence of a discontinuous reduction in mortality rates for any of the 6 causes. The top 6 causes and their associated three digit ICD-9 CM codes (in parentheses) are: ischemic heart disease (410-414), lung cancer (162), chronic obstructive pulmonary disease (490-496), cerebrovascular disease (430-438), diabetes (250), and pneumonia (480-496).

and predicted mortality is typically a little larger.[41] These results provide no evidence that Medicare coverage leads to a discrete reduction in mortality at ages 66 and 67, and point instead toward the difficulty of predicting the age profiles of mortality from the death rates of younger people.[42]

As an alternate and perhaps more straightforward way of examining the changes in mortality rates, we examine the age profile in the year-to-year percent changes in the mortality rate. In Figure 15, we see that there is no evidence of a deceleration in the mortality rate at age 65. This result stands in sharp contrast to findings reported by Lichtenberg (2001), who uses life-table death probabilities constructed by the Social Security Administration and finds a short-term reduction in the growth rate of mortality between ages 65 and 69. The SSA life tables are primarily intended for use in projecting the long-term survival rates of the US population and are generally not suitable for examining changes in the derivative of mortality rates. In particular, two methodological issues make the SSA life tables unsuitable for this type of analysis. First, SSA uses Vital Statistics and Census data to construct death probabilities before age 65, but switches to using death data from the Medicare program after age 65.[43] If the slope of the mortality profile at 65 happens to differ somewhat between the two data series, then splicing them together will lead to a spurious change in the first derivative at exactly age 65. Second, SSA uses osculatory interpolation to produce smoothly trending estimates within five-year age groups. In order to prevent discontinuities at the seams between age groups, this method forces the first derivatives of the interpolated series to be equal at the seams between age groups (seams

[41] The differences between actual and predicted mortality rates become more pronounced at older ages as we project further out-of-sample from age 64. Basing the projections on higher order polynomials does not solve this problem.
[42] One obvious issue is the presence of cohort effects, which would confound the extrapolation exercise.
[43] The methodology used by SSA is described, in detail, in Bell et al. (1992).

occur at 60, 65, 70, etc.), making it appear as if the derivative changes smoothly across the seams, and thus obscuring any spurious changes in the derivative caused by the change of data series.[44] More generally, interpolated data pose a problem for research designs based on the occurrence of discontinuities since interpolation is designed to smooth out such irregularities, even when they are real.

Due to the difficulties in estimating mortality rates for older people from the age profiles for younger people, we turn to an alternative based on plausible comparison groups. In Figure 16, we compare mortality rates for 50-to-80 year olds in the five years before and after Medicare was implemented in 1966. We do not see a discernable pre-post difference in mortality for men. For women we see a significant reduction in mortality rates in the later period. However, the reductions occur for women as young as 62, suggesting that the declining mortality rates are the result of technological improvements or cohort differences rather than Medicare. There are two obvious limitations with the simple comparisons in Figure 16. First, since the mortality rates are typically decreasing over time it is possible that small improvements due to Medicare may be hidden by the greater improvements due to other causes. Second, this particular comparison is limited in its ability to pick up the impact of Medicare because older people in the post-1965 sample have only been exposed to a few years of Medicare coverage.

To sidestep this problem we compare mortality rates in the United States and Canada. Canada is a plausible counterfactual since although the two countries are generally similar, Canadians have universal health insurance coverage at all ages. Canadian death rates are lower than those in the U.S., however, so some adjustment is needed to predict the profile of U.S. rates in the absence of Medicare. After some experimentation, we found that U.S. death rates before

[44] For an overview of osculatory interpolation, see Shyrock and Siegel (1980), pp. 694-702 or Smith (1992), pp. 27-34.

65 are quite similar to those of Canadians 2 years older. Figure 17 therefore shows U.S. mortality rates by gender, along with Canadian rates that have been shifted left by 2 years.[45] Use of the adjusted Canadian death rates as a counterfactual shows no evidence of a discrete change in US death rates at age 65 for either men or women, although it should be noted that age-adjusted Canadian profiles do not perfectly track the US profiles between the ages of 50 and 64, so this comparison is unlikely to reveal small changes in mortality rates associated with Medicare eligibility.

Although our results suggest that Medicare has little impact on mortality rates, either at age 65 or over the longer run, we believe they should be interpreted with caution. The mortality rates we have examined are for large groups, and it is quite possible that there are effects for subgroups that are masked by the aggregation. This is a particular problem because the increases in access to care documented earlier in the paper affect only a small fraction of the population. The precision of our comparisons is limited by the difficulty of obtaining precise estimates of mortality patterns in the absence of Medicare. It is thus unlikely that our methods could detect anything other than a very large effect.

IX. Summary of Patterns Across Groups

To summarize our findings, Table 12 presents estimates of equation (5), relating the estimated reduced form effects of reaching age 65 across different subgroups to the estimated rise in net health insurance coverage at age 65 for each subgroup. We estimate the models across 7 subgroups: 3 ethnicity groups and 4 ethnicity/education groups.[46] Each row of the table corresponds to a different outcome. For example, row 1 shows the relationship between the

[45] The death rates for these comparisons come from the Human Mortality Database at UC Berkeley. We also tried raising the Canadian mortality rates at each age so that the rates among 60-64 year olds matched, but this resulted in a very poor fit among 50-60 year olds.

[46] The groups are not mutually exclusive so the standard errors are understated. The model should be estimated by generalized least squares using the inverse covariance matrix between the 7 estimates as a weighting matrix.

changes in the probability of delaying medical care at any time in the past year to the changes in insurance coverage. The coefficient estimates reported in column 1 correspond to estimates of the coefficient d_1 in equation (5). Under the assumption of a constant causal effect of coverage, this is an estimate of δ (the causal effect of insurance coverage). Column 2 reports the R-squared coefficients for the equations. As noted in our earlier discussion, these should be relatively high if the discontinuity of the outcome variable at age 65 is solely attributable to the rise in insurance coverage. Column 3 shows the mean gap in the outcome at ages 63-64 between more educated whites and less educated minorities: this is a simple summary of the SES gradient for the outcome among the near-elderly population. Finally column 4 shows the estimated fraction of this gap that is closed after the availability of Medicare, estimated by multiplying the estimate of d_1 by 13.54% (the estimated relative jump in coverage from column 3 of Table 3).

Looking first at the three self-reported measures of access, the relative sizes of the jumps in access across subgroups are systematically correlated with the jumps in coverage. Reaching the Medicare eligibility age is estimated to close 40-80 percent of the inter-group disparity in the three measures. The same conclusion holds with respect to the probability of a doctor visit in the past year: 84 percent of the variation across groups is attributable to differential rises in insurance coverage, and over 100% of the inter-group gap among 63-64 year olds is closed after 65. This contrasts sharply with the estimated changes in the probability of a hospital stay, which are essentially unrelated to the increase in insurance coverage.

Results for the four preventative care outcomes – flu shot in the past year, cholesterol test in the past 2 years, mammogram in the past 2 years, and prostate test in the past 2 years – are weaker. Variation in the size of the discontinuities in these outcomes at age 65 is not very highly correlated with the discontinuities in insurance coverage, but the point estimates of the coefficients in column 1 suggest eligibility for Medicare would be expected to close 15-30 percent of the SES gradient in preventative care.

Finally, the last row of the table looks at self-reported health. The estimated jumps in health at age 65 (from the ordered probit specification in Table 9) are reasonably highly correlated with the corresponding jumps in insurance coverage, with an R-squared coefficient of 0.66. Although Medicare eligibility is estimated to have a narrowing effect on inter-group disparities in health, the predicted effect is to close only about 12 percent of the gap among the near-elderly.

X. Conclusions

In this paper, we use the discrete changes in health insurance coverage at age 65 generated by the rules of the Medicare program to identify the impact of health insurance coverage on health related behaviors and health outcomes. Medicare eligibility is associated with a sharp increase in average coverage rates at age 65 and a narrowing in coverage disparities across different groups in the U.S. population. Variation in the relative impact of the program provides a way to test that it is health insurance coverage *per se* that is responsible for the changes in health care utilization and health that occur at age 65, rather than other features such as the relative generosity of Medicare reimbursement schedules.

Our estimates show that insurance coverage has a significant causal effect on self-reported access to health care and on health care utilization. Race and education groups that experience the largest gains in insurance coverage at age 65 experience large reductions in the probability of delaying or not receiving medical care, and relative increases in the probability of an annual doctor visit. Evidence for an impact of insurance coverage on medical screenings and preventive care is less clear-cut, although this is partly a reflection of data limitations. We also find large and precisely estimated increases in hospital admissions at age 65, with the biggest increases for discretionary procedures like hip and knee replacements and bypass surgeries. Unlike doctor visits, the rise in hospital admissions tends to be larger for groups with higher insurance coverage prior to age 65. Thus, the roughly 10 percent rise in hospitalization rates between 64 and 65 year olds appears to be a result of differences between Medicare and private insurance coverage, rather than of the rise in insurance coverage at age 65.

The impact of Medicare eligibility on health outcomes is harder to assess, both because of difficulties in measuring health, and because health is less likely to change discretely in response to insurance coverage. Perhaps surprisingly, we find a statistically significant impact of reaching age 65 on self-reported health, with the largest gains among the education and race groups that experience the largest increases in insurance coverage at age 65. On the other hand, we find no evidence of a discrete change in mortality rates at 65, nor do we see any shift in the rate of growth of mortality after 65. These findings have to interpreted cautiously since it is difficult to identify a plausible comparison group for post-65 mortality rates in the absence of Medicare. Taken as a whole, we believe our findings point to a significant but relatively modest impact of health insurance coverage on health.

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Figure 1: Health Insurance Coverage Rates by Age, 1992-2001 NHIS

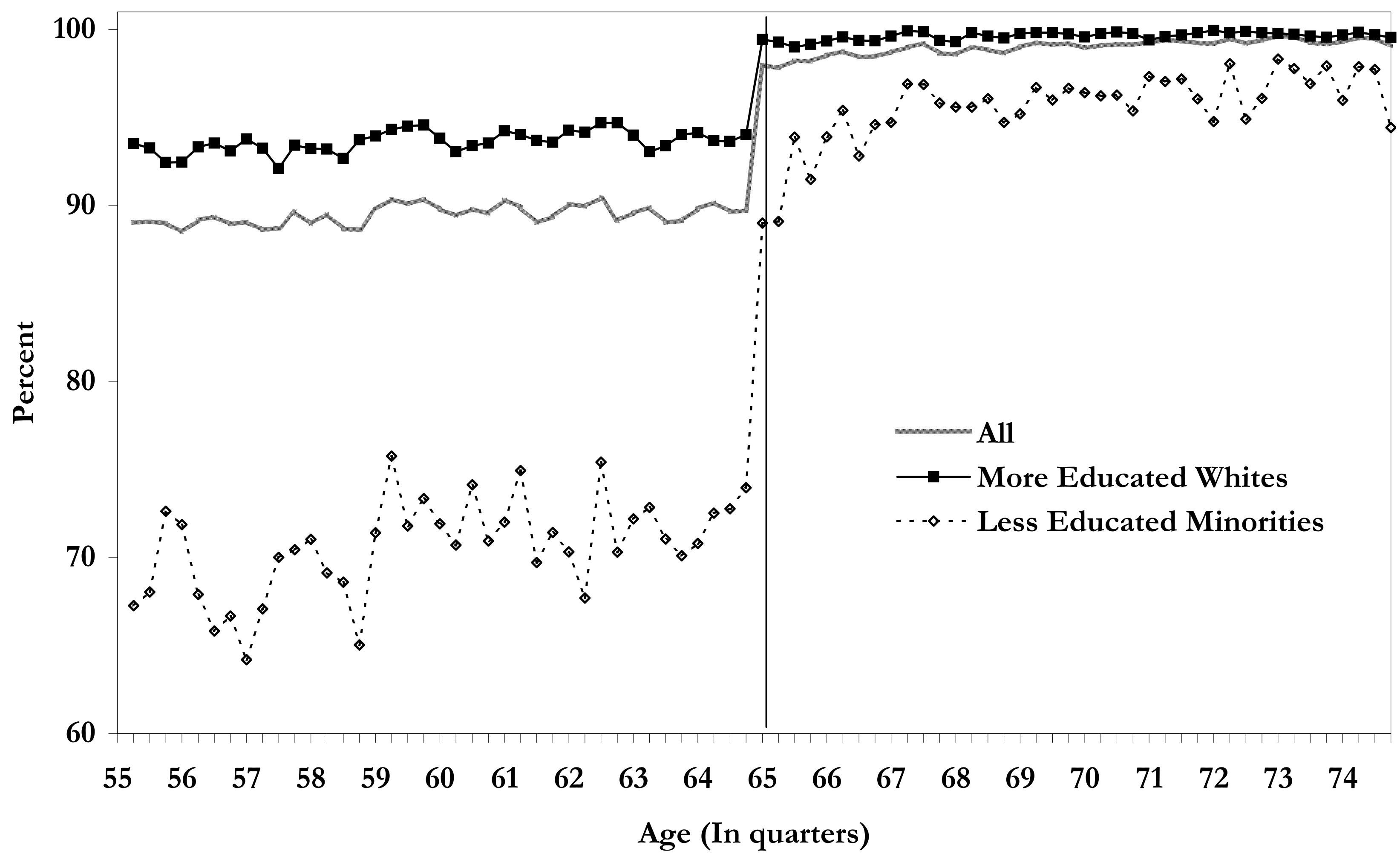

Figure 2: Medicare Coverage Rates by Age, 1992-2001 NHIS

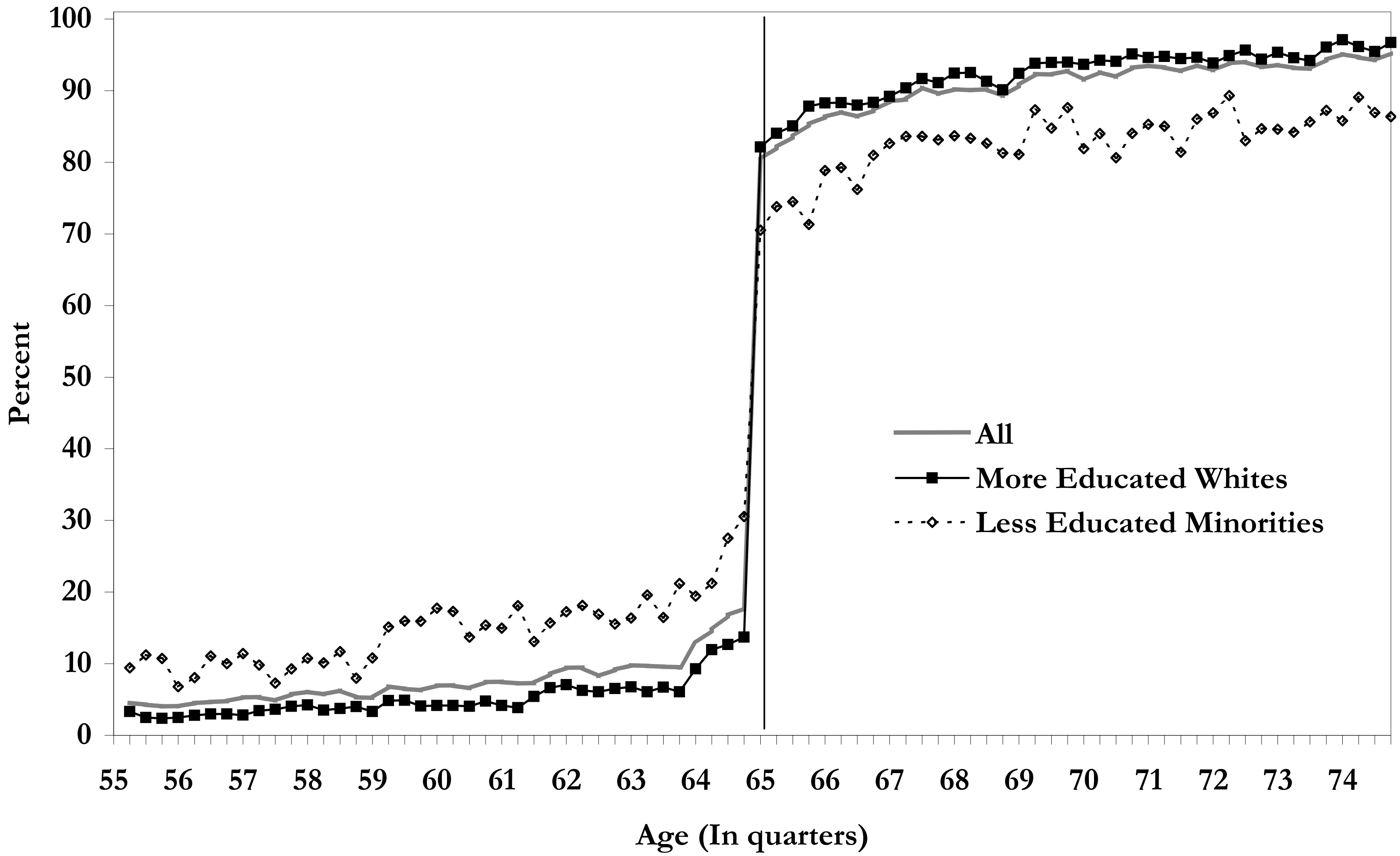

Figure 3: Health Insurance Coverage and Employment Rates of Men by Age

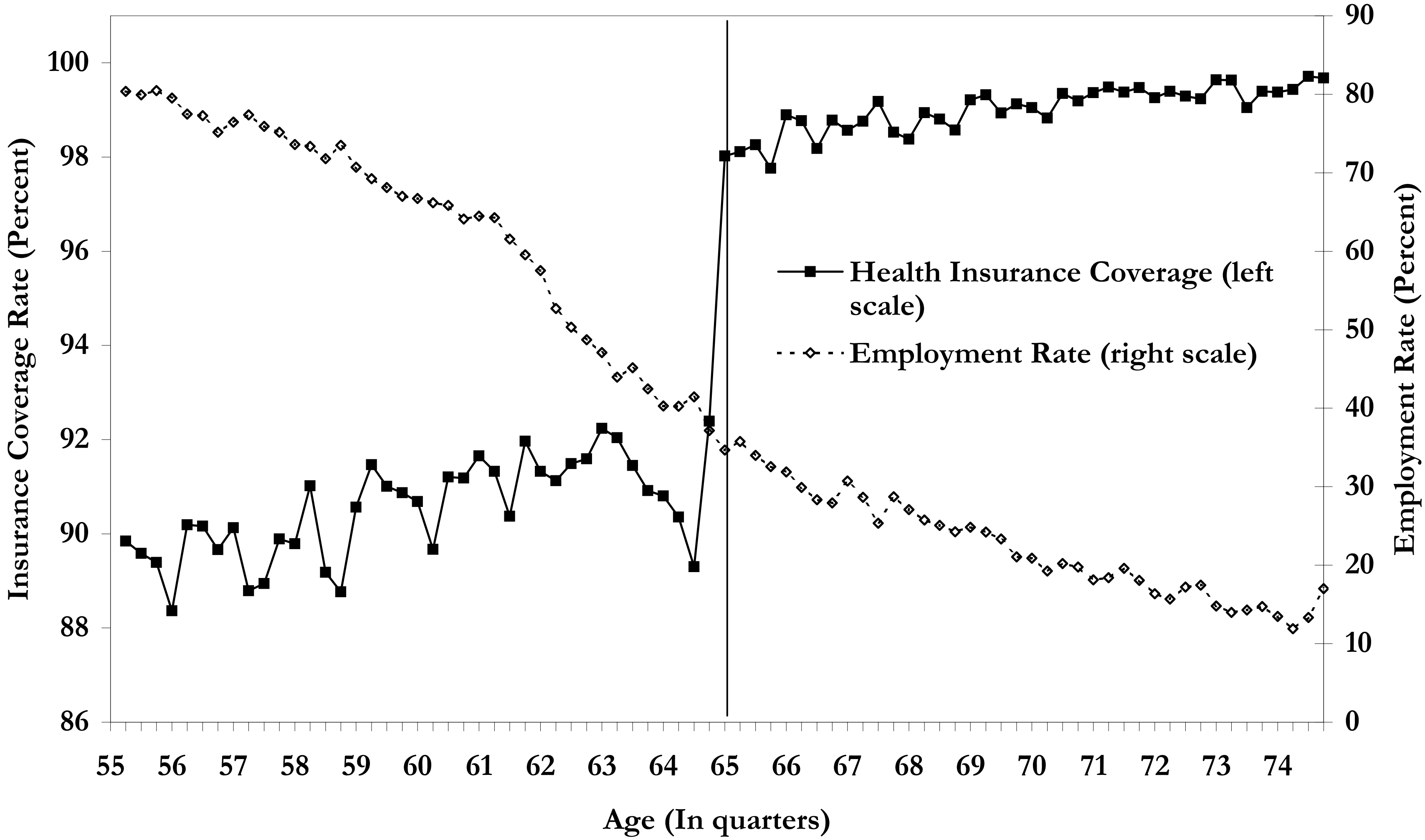

Figure 4: Percent Who Delayed Medical Care Last Year for Cost Reasons

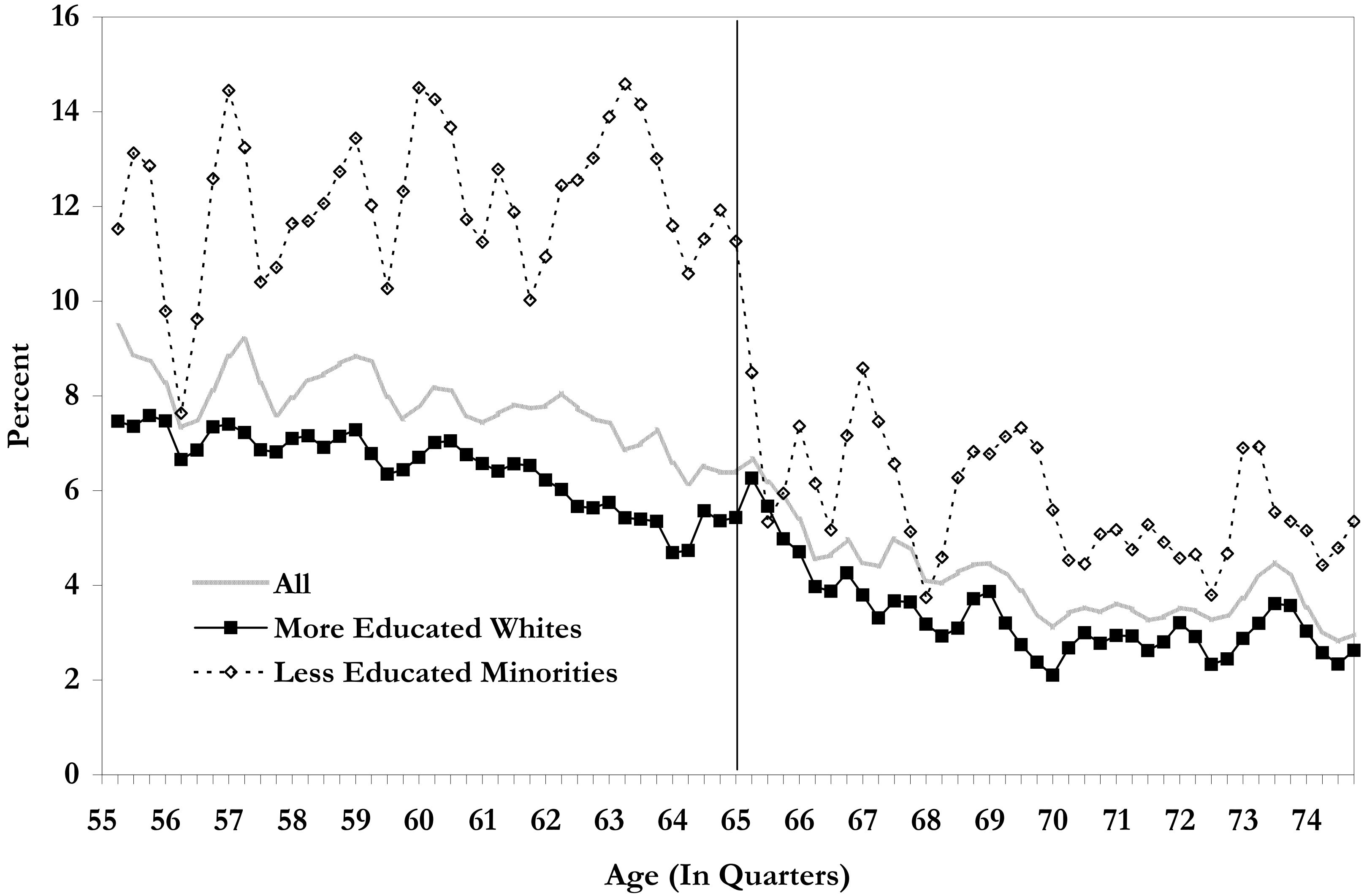

Figure 5a: Percent Who Did Not Get Medical Care Last Year for Cost Reasons (NHIS)

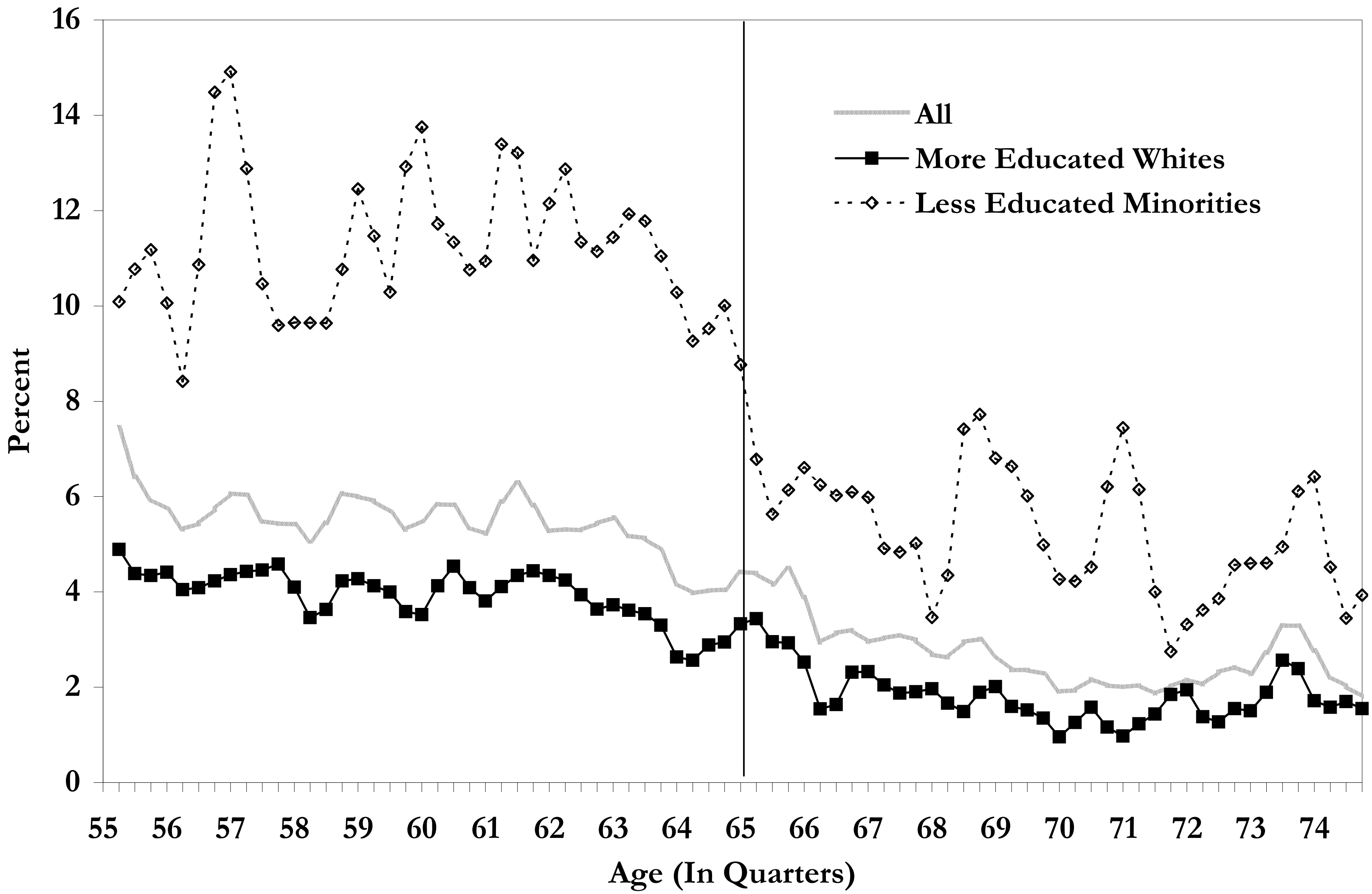

Figure 5b: Percent Who Did Not Get Care for Cost Reasons (BRFSS)

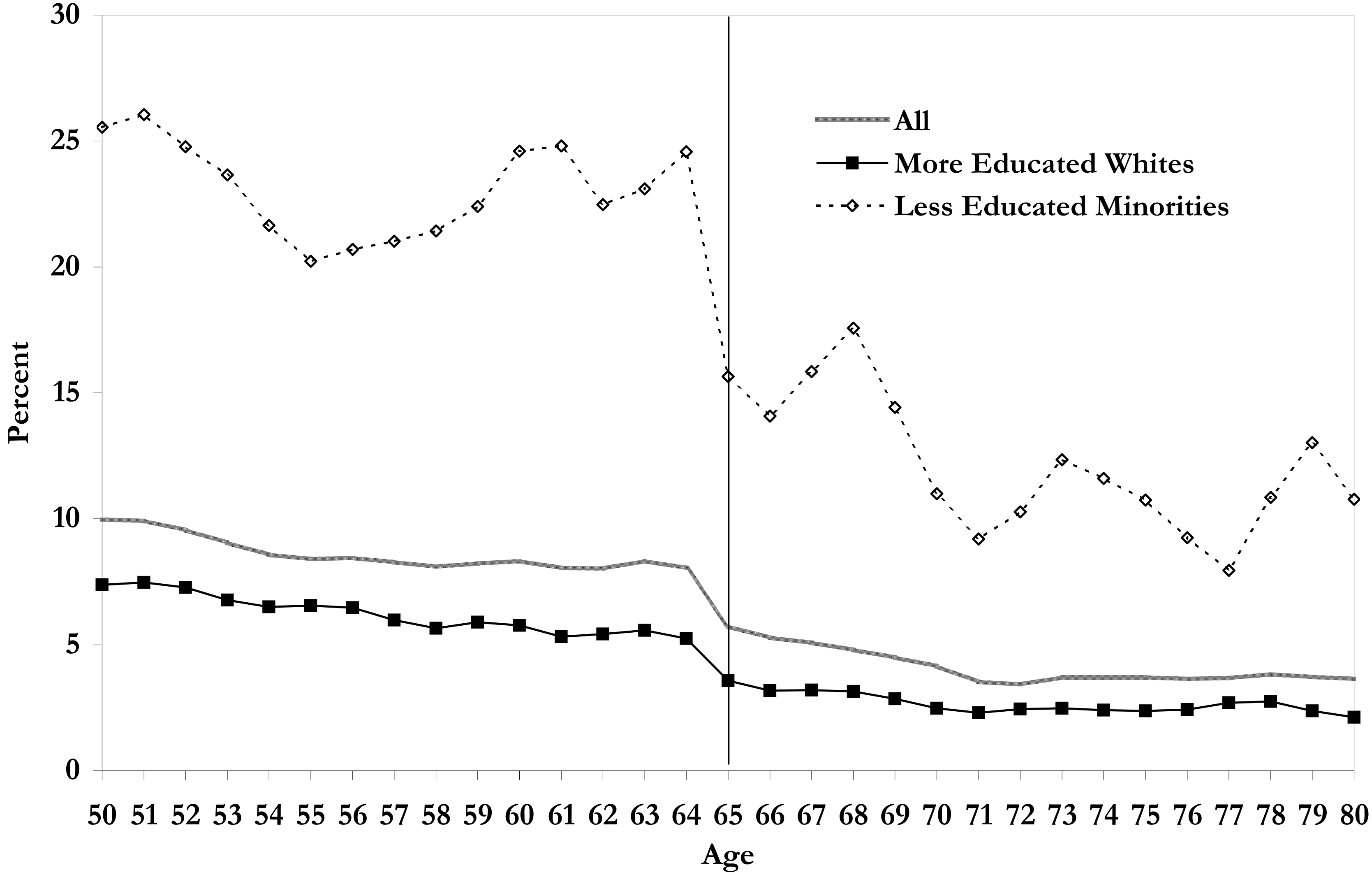

Figure 6: Percent with At Least One Doctor Visit in Past Year by Age, 1992-2001 NHIS

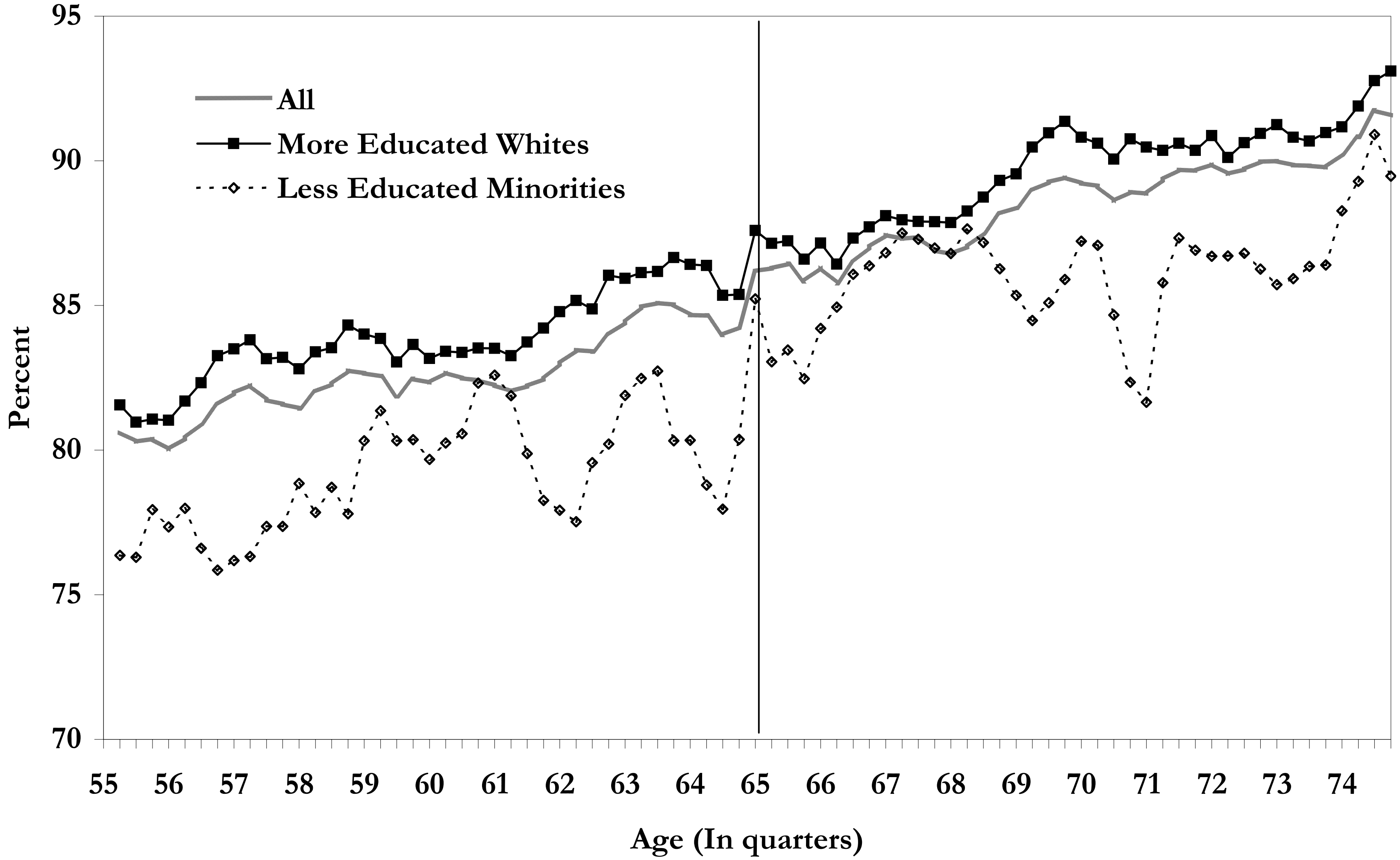

Figure 7: Percent with One or More Hopital Stays in Past Year by Age, 1992-2001 NHIS

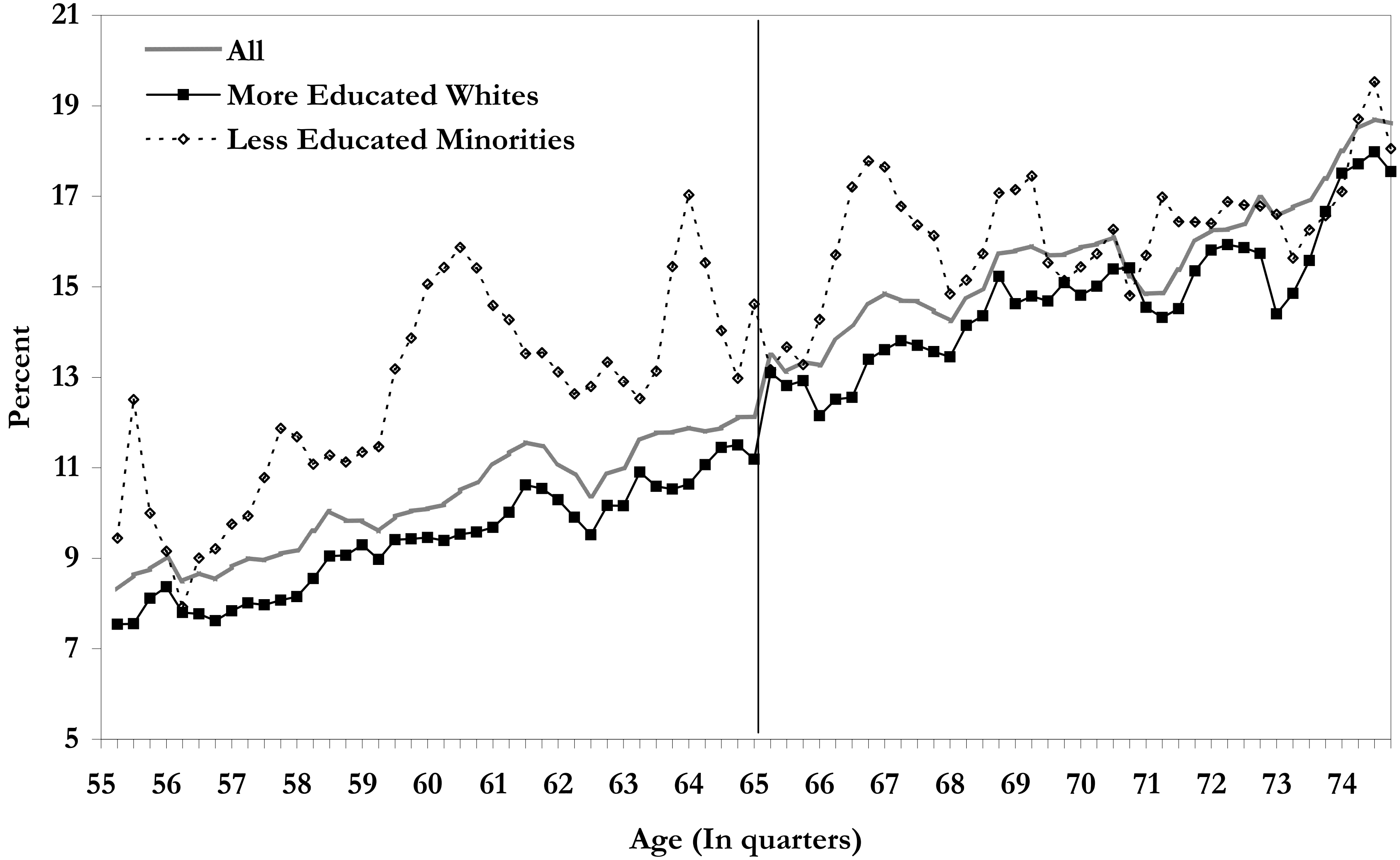

Figure 8: Percent of Women with Mammogram in Past 2 Years, 1999-2002 BRFSS

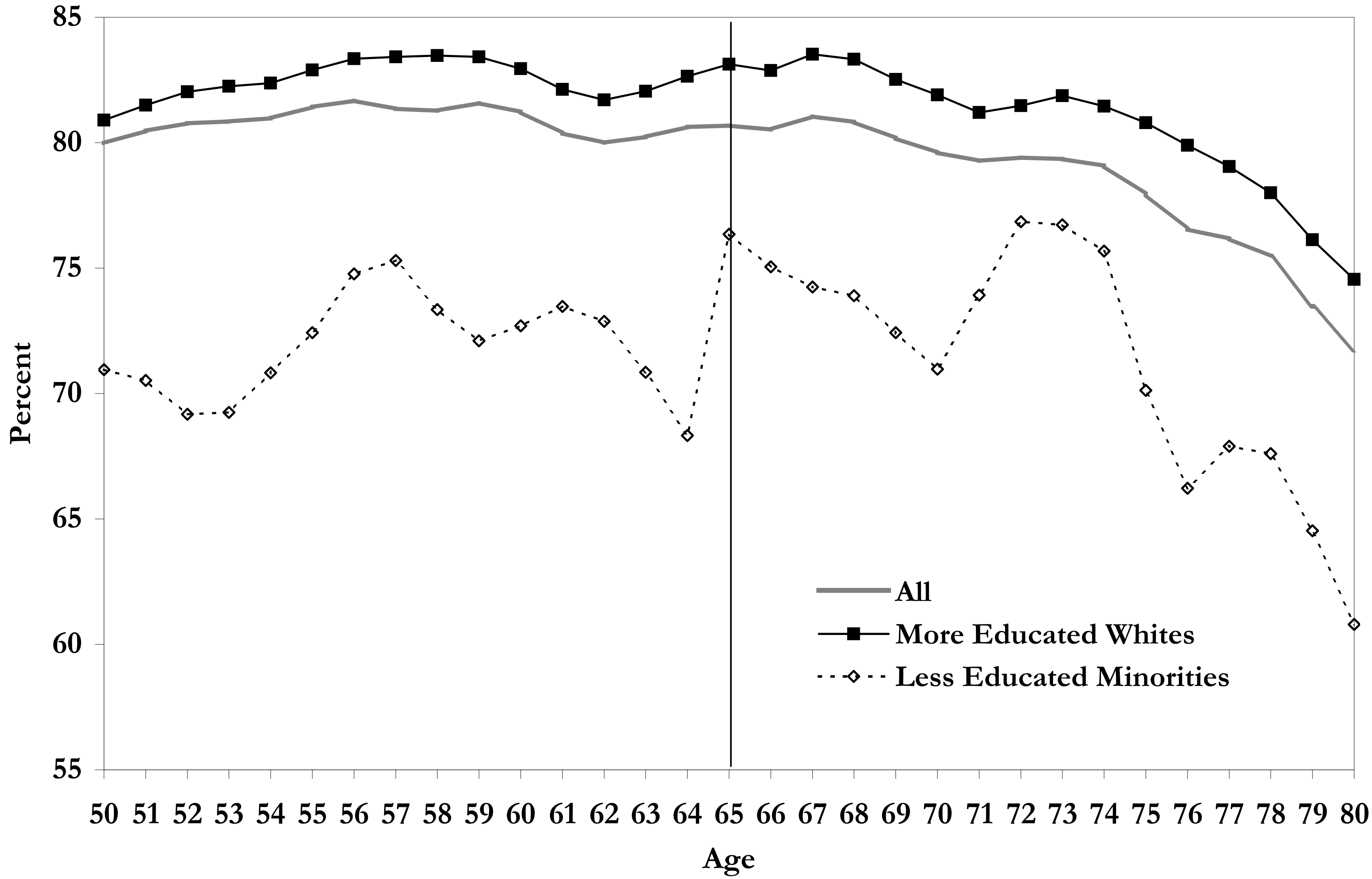

Figure 9: Number of Hospital Admissions by Age in California and Florida

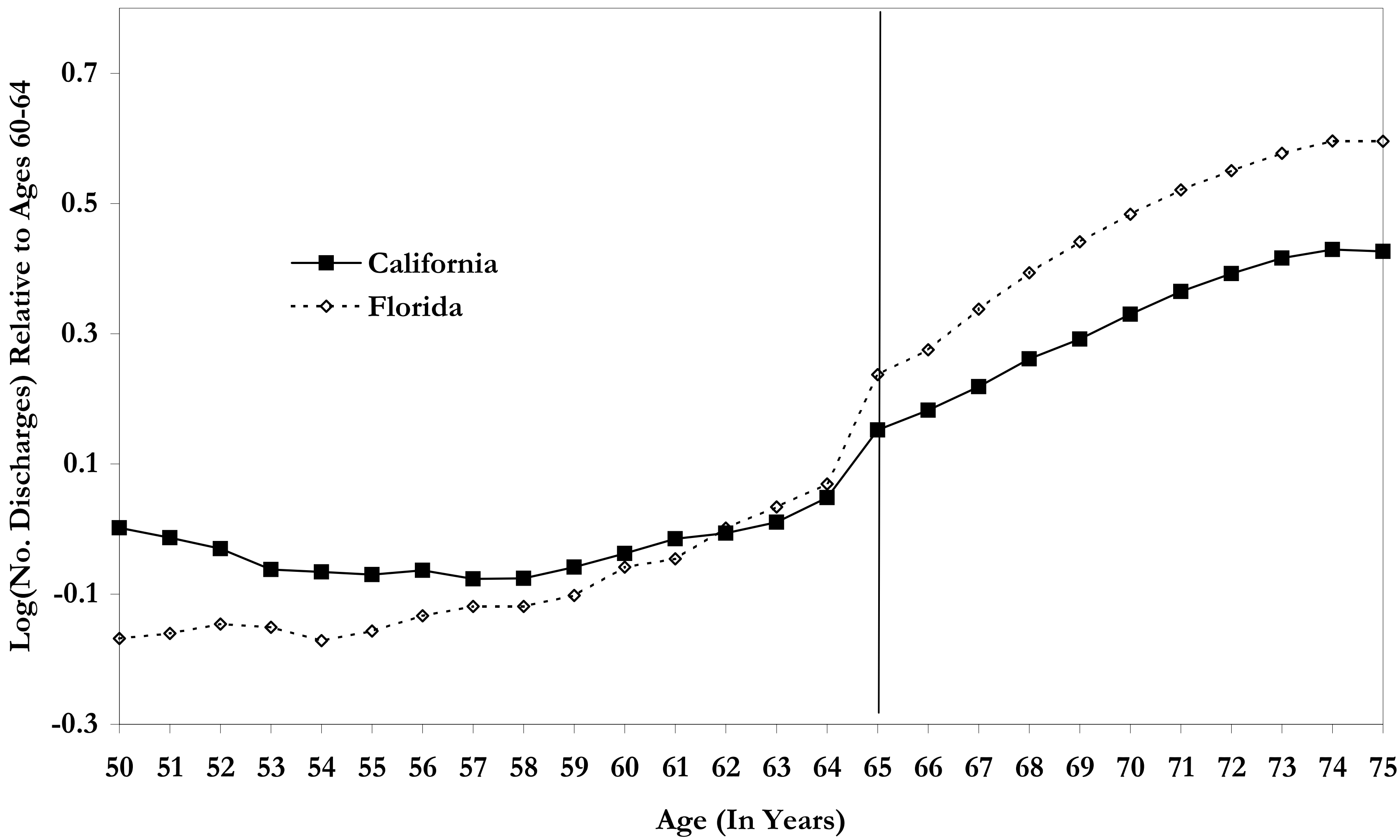

Figure 10: Age Profiles of the Number of Hospital Admissions by Ethnicity

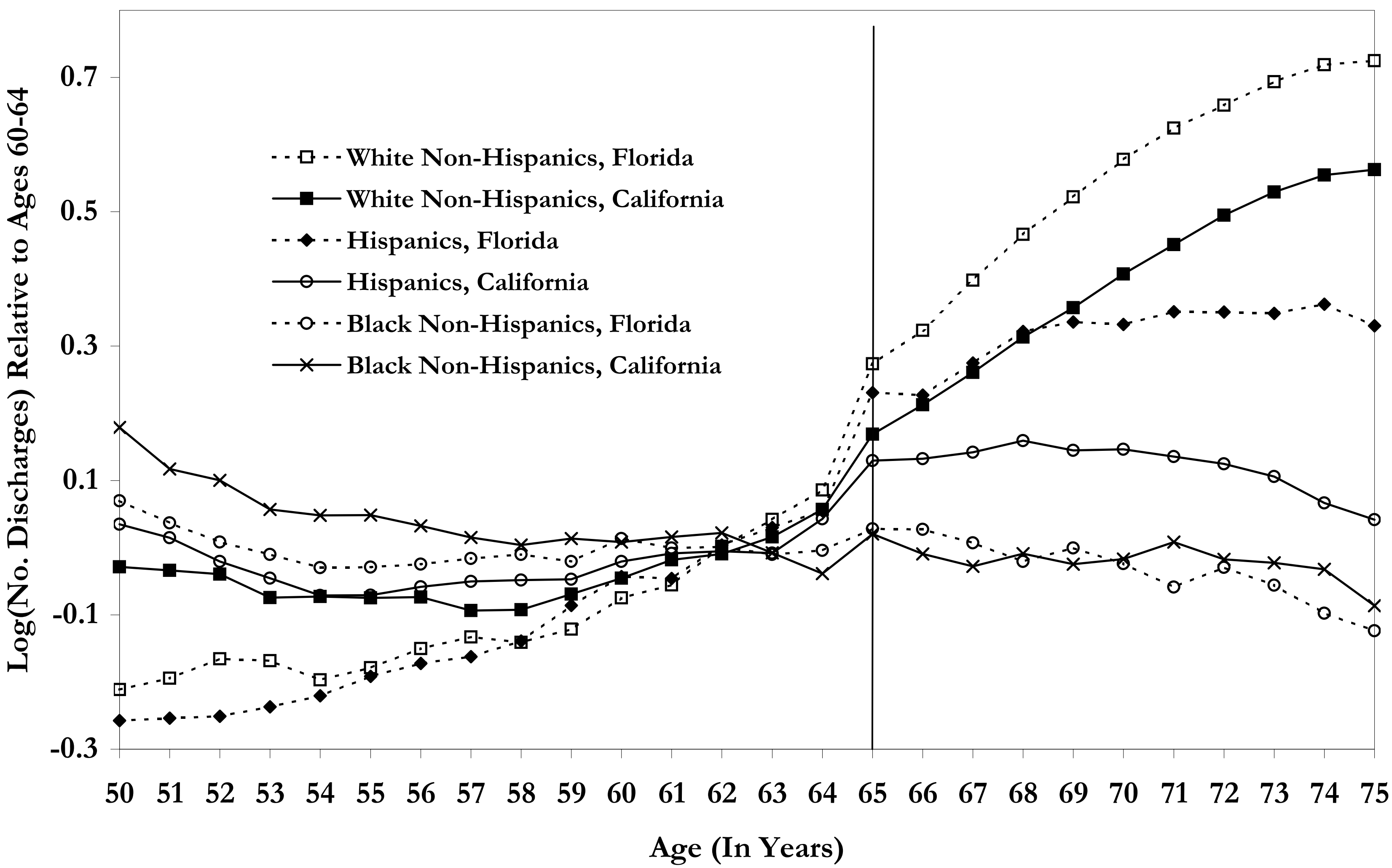

Figure 11: Age Profiles of the Number of Hospital Admissions by Insurance Coverage

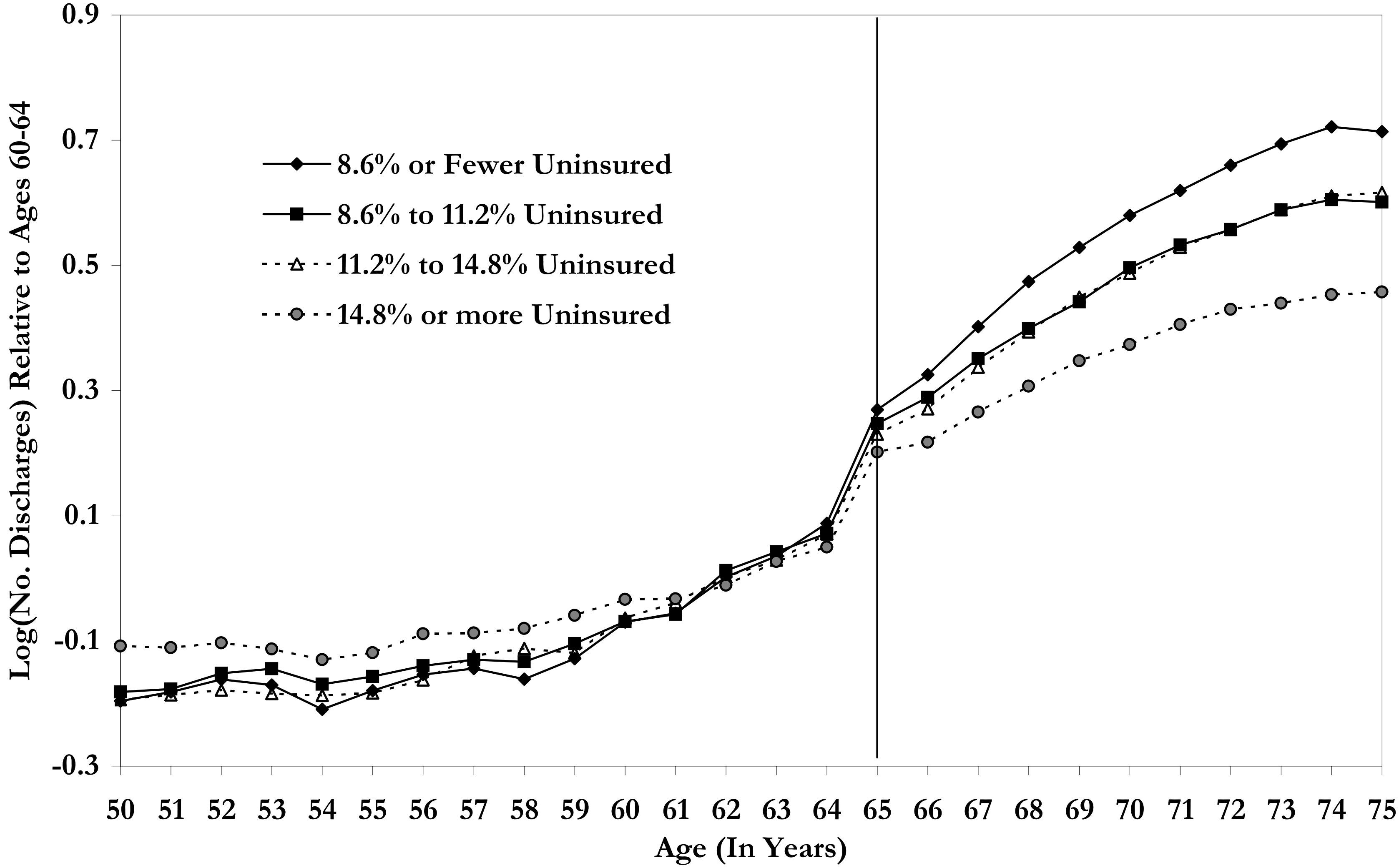

Figure 12: California Hospital Admissions for 6 Common Diagnoses (By 3 Digit ICD-9)

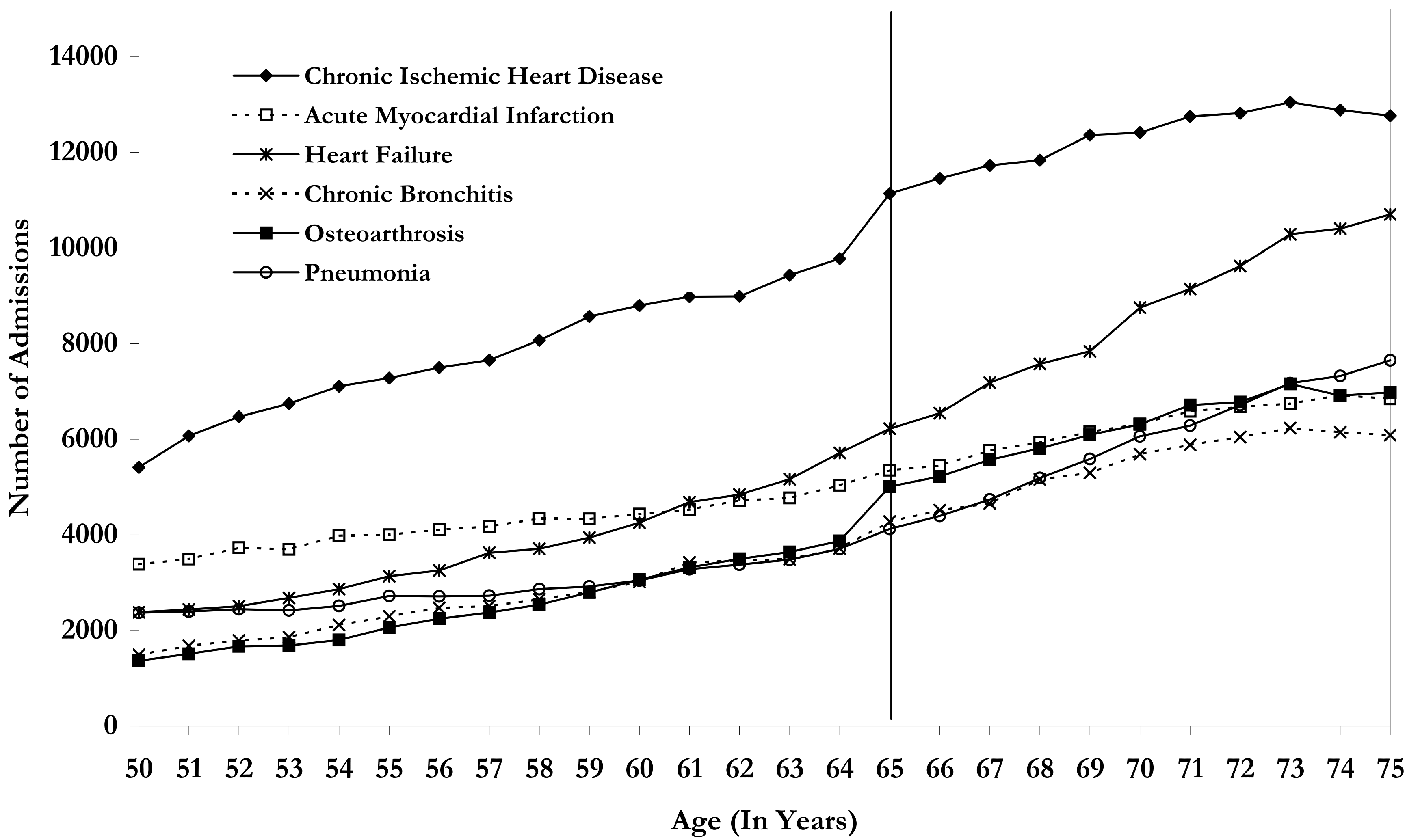

Figure 13: Percent in Good, Very Good, or Excellent Health by Age, 1992-2001 NHIS

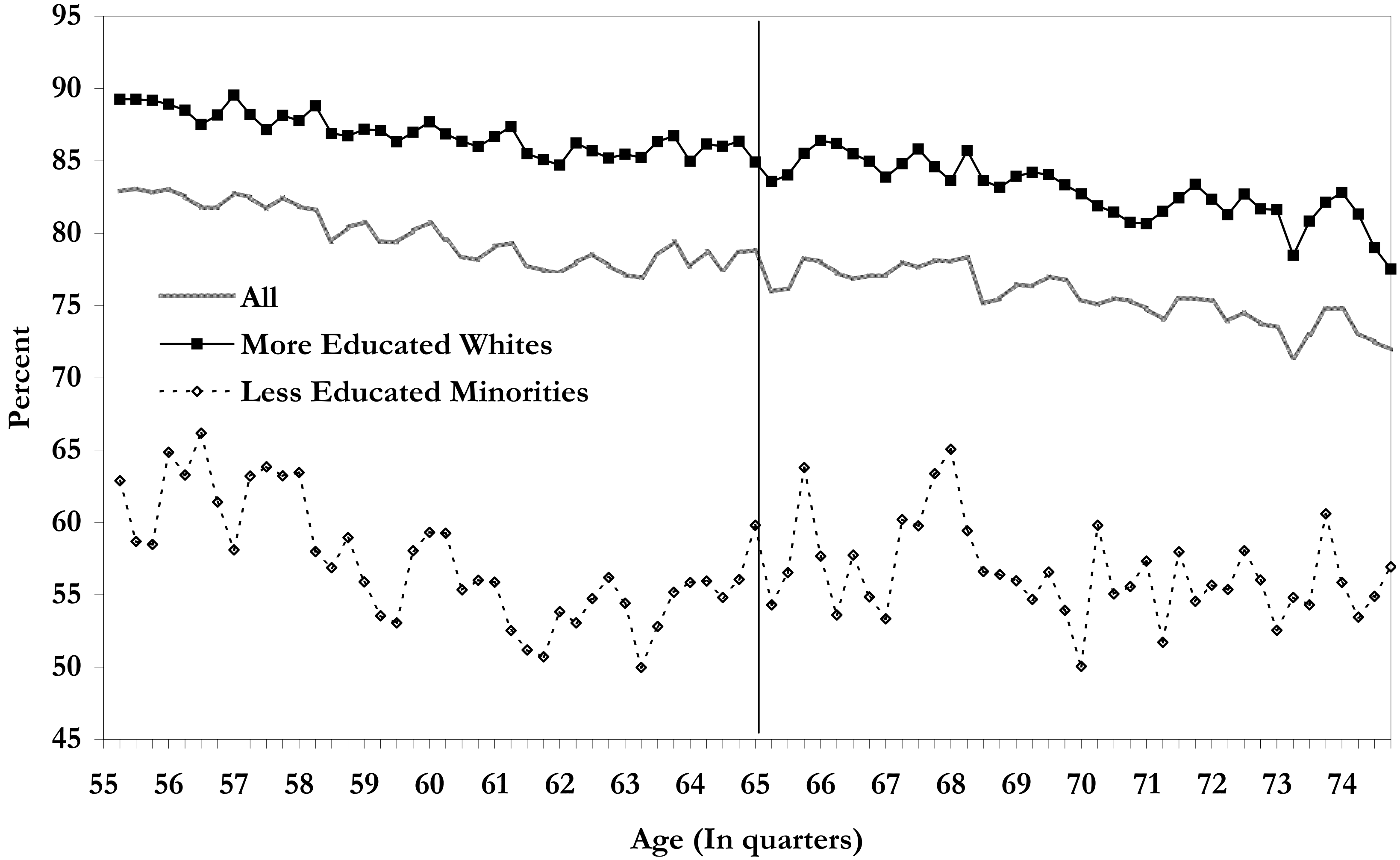

Figure 14. Age-Specific Death Rates by Sex and Race

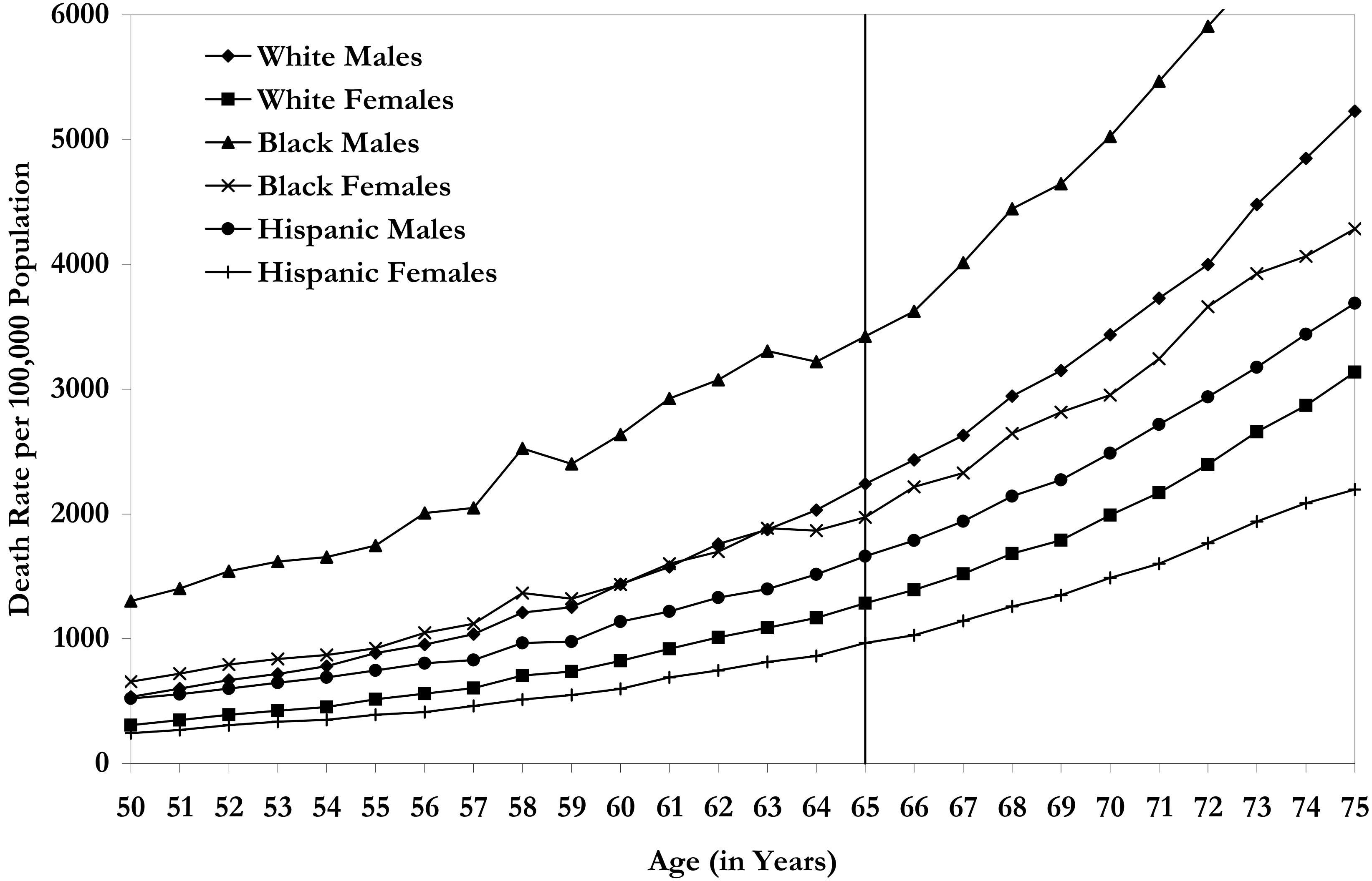

Figure 15. Percent Change in Age-Specific Death Rates by Sex

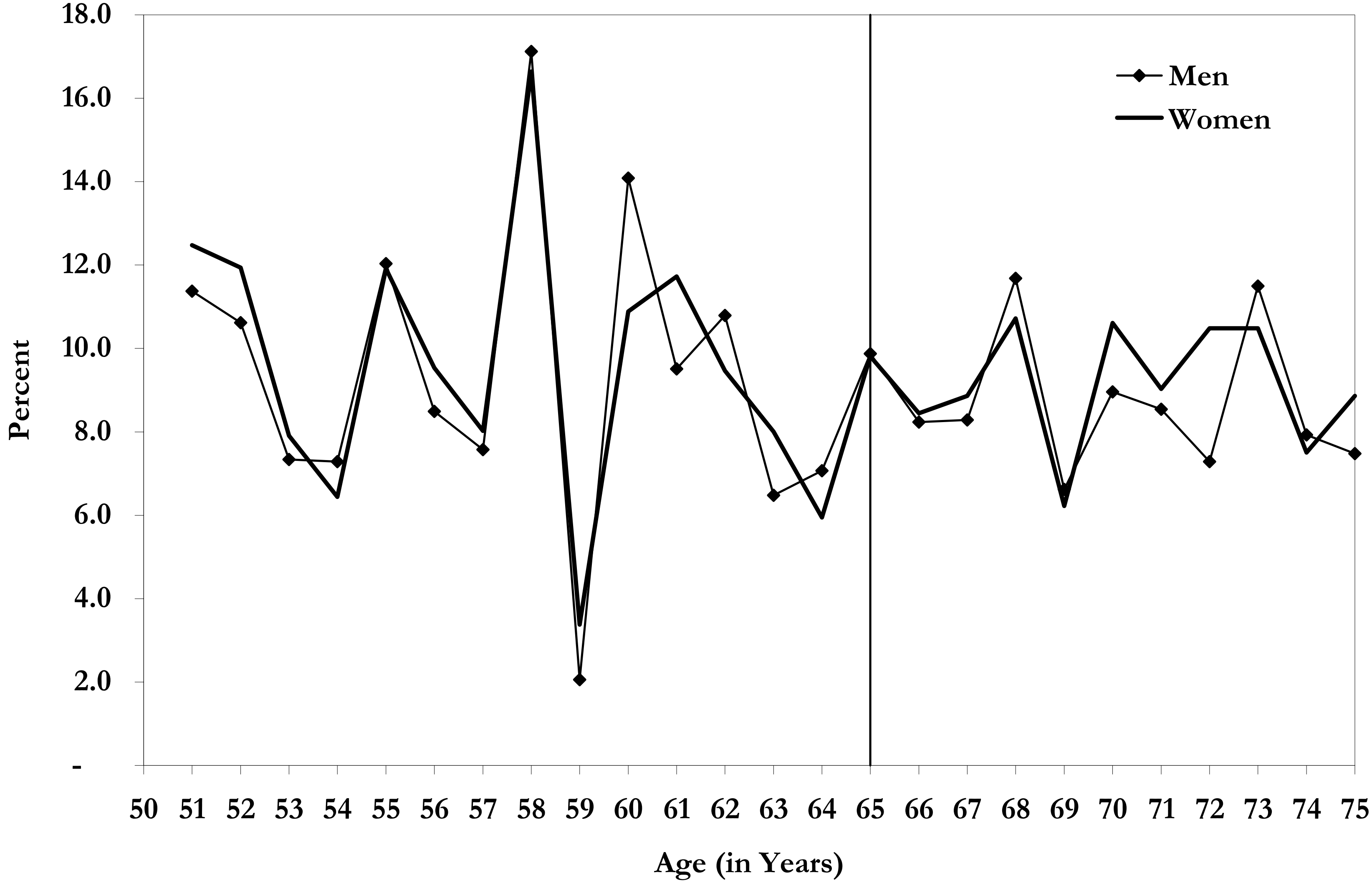

Figure 16. Death Rates in the U.S. before and after 1966

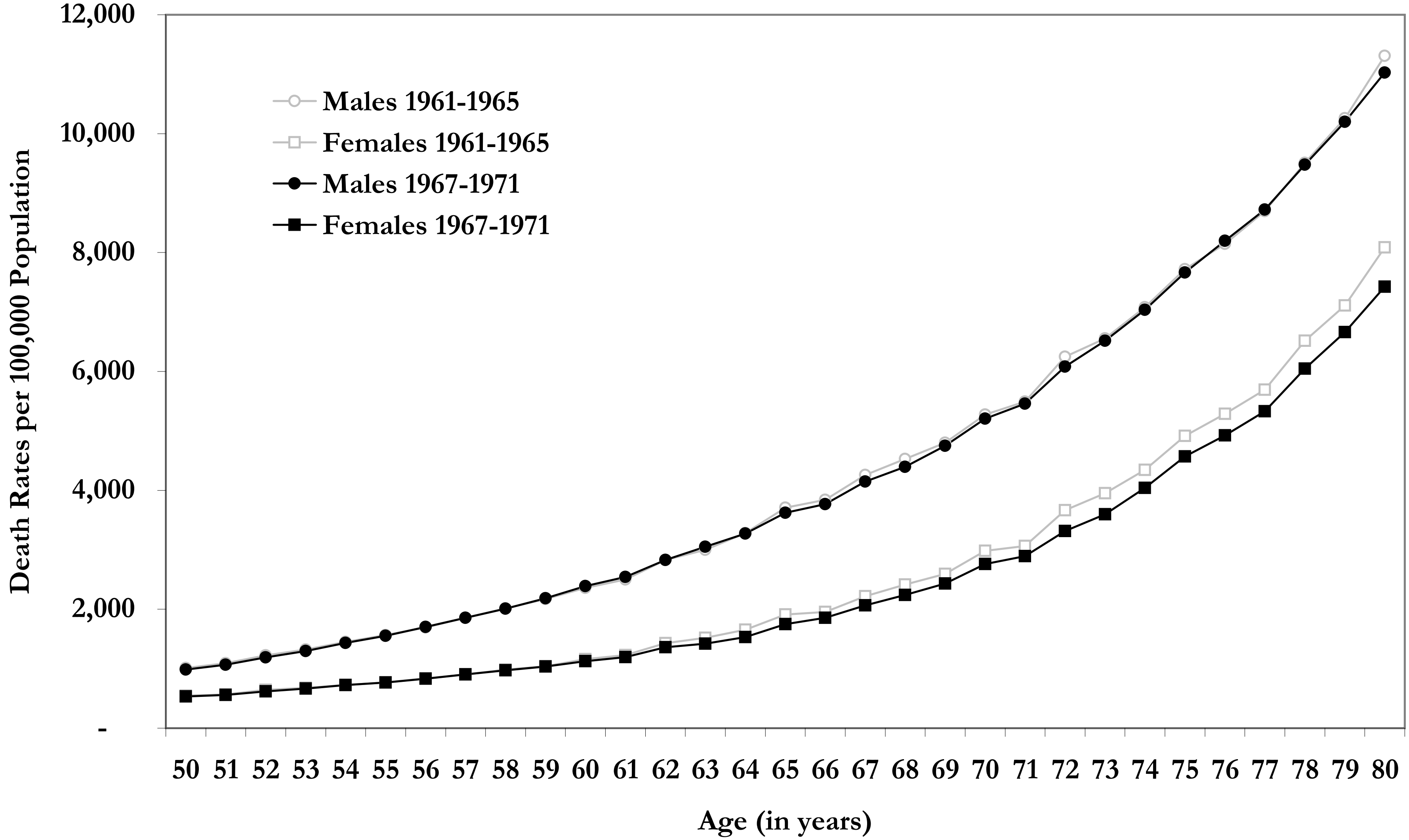

Figure 17. Unadjusted Death Rates for the United States and Age-Shifted Death Rates for Canada, 1990-1994

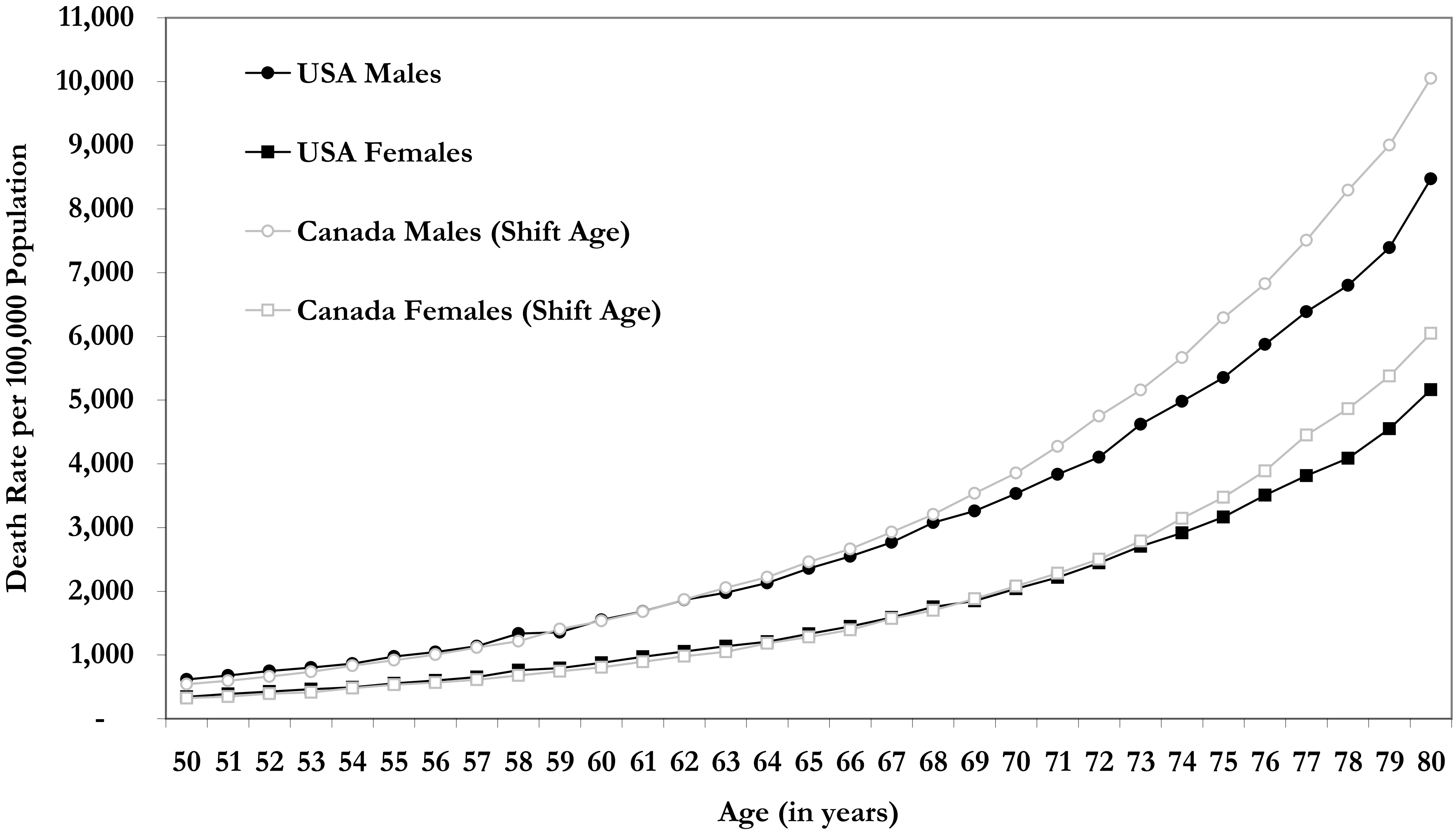

Table 1: Characteristics of People Age 62-64 With and Without Health Insurance

	Overall Sample	Subsample With Insurance	Subsample Without Insurance	T-ratio
Have Health Insurance	90.1	100.0	0.0	--
Female	51.8	51.2	58.3	4.60
Married	72.6	74.2	58.0	10.65
Working	40.9	41.2	38.4	1.80
Poor (Family Income<Pov. Line)	7.1	5.8	19.3	11.37
White Non-Hispanic	81.1	83.1	62.6	13.94
Black Non-Hispanic	8.9	8.4	13.3	4.69
Hispanic	7.0	5.7	19.1	11.39
Other Race Non-Hispanic	3.0	2.8	5.0	3.30
High School Dropout	24.2	21.3	50.8	19.26
High School, No College	35.0	35.8	28.4	5.21
Some College	20.7	21.6	13.1	7.82
4 Years College or More	20.0	21.4	7.7	15.19
Daily Smoker	14	13.2	20.5	
Any Exercise in Past 30 Days	70.2	71.5	60.9	9.49
Overweight (BMI over 25.0)	67.6	67.4	69.2	1.19
Obese (BMI over 30)	25.1	24.7	28.0	2.13
Have a Usual Place of Preventative Care	94.2	96.3	74.6	11.59
Delayed Care Last Year for Cost Reasons	7.1	4.8	28.1	17.44
Saw Doctor At Least Once Last Year	84.4	86.6	65.7	15.42
Had Routine Checkup Last Year	81.6	84.1	62.3	8.81
Overnight Stay in Hospital Last Year	11.3	11.7	7.5	6.22
Had Flu Shot Last Year	46.6	48.7	31.4	9.88
Ever Had Pneumonia Shot	28.6	29.5	21.7	5.10
Had Cholesterol Check in Last 2 Years	83.1	85.8	61.6	10.38
Had Mammogram in Last 2 Years	80.5	84.1	56.6	12.09
Had Pap Smear in Last 2 Years	71.9	74.5	55.1	8.34
Had Clinical Breast Exam in Last 2 Years	78.7	81.6	59.7	9.57
Had Prostate-Specific Antigen Test in Last 2 Yrs	69.4	72.0	46.9	6.64
Had Digital Rectal Prostate Exam in Last 2 Years	69.4	72.1	45.9	7.06
Ever Diagnosed with Hypertension	45.5	46.1	40.9	2.37
Ever Diagnosed with Diabetes	14.4	14.4	15.1	0.44
Ever Diagnosed with Heart-Related Problems	19.0	19.6	14.0	3.63
In Good, Very Good, Excellent Health	79.4	79.9	74.1	4.24

Notes: Except as noted, means are based on data from pooled 1997-2001 NHIS. Percent who saw a doctor in past year and percent with a hospital stay in past year come from pooled 1992-2001 NHIS. Percent with a routine doctor visit, cholesterol test, mammogram, pap smear, clinical breast exam, PSA test, digital rectal test, any exercise in past month, overweight, and obese are based on data from pooled 1998-2002 BRFSS. Heart-Related Problems include coronary heart disease, angina pectoris, and "any [other] kind of heart condition or heart disease".

Table 2: Differences in Health Care Access/Utilization by Group and Insurance Status (62-64 Year Olds)

	Percent Insured	Delayed Care for Cost Reasons Last Year:			Saw Doctor Last Year:			Hosp. Stay Last Year:			Had Mammogram in Past 2 Years:			Had Cholesterol Test in Past 2 Years:		
		Ins.	Unins.	T-ratio	Ins.	Unins.	T-ratio	Ins.	Unins.	T-ratio	Ins.	Unins.	T-ratio	Ins.	Unins.	T-ratio
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
All	90.1	4.8	28.1	17.4	86.6	65.7	15.4	11.7	7.5	6.2	84.1	56.6	12.1	85.8	61.6	10.4
High Education White Nonhispanic	94.4	4.1	30.1	10.2	87.3	67.6	8.9	10.6	7.7	2.5	84.8	55.2	10.7	87.3	64.9	7.8
Low Education White Nonhispanic	83.6	7.1	30.7	7.4	84.7	61.8	7.9	15.2	7.0	5.8	74.2	47.4	6.0	78.9	45.3	6.2
High Education Minority	88.1	4.2	26.0	6.4	85.6	68.5	4.8	10.7	4.7	3.9	89.8	69.1	3.4	86.3	60.7	4.0
Low Education Minority	71.4	7.7	26.3	8.2	85.7	65.7	7.6	15.4	9.1	4.1	77.4	57.9	2.7	78.5	65.6	1.9

Note: See note to Table 1. Entries under "Ins." columns are means for subgroup with health insurance. Entries under "Unins." column are means for subgroup without insurance. High education refers to high school diploma or more. Minority refers to Hispanics, blacks, and members of other non-white racial groups.

Table 3: Regression Discontinuity Estimates of Change in Health Insurance Coverage at Age 65

	Model fit to Aggregrated Age Cells (1)	Models fit to Micro Data: Linear Prob. no controls (2)	Linear Prob. w/ controls (3)	Probit w/ controls (4)	Linear Prob. Model for Medicare (5)
All	8.41	8.41	8.60	6.05	67.32
	(0.30)	(0.26)	(0.24)	(0.20)	(1.49)
By Ethnicity/Education:					
High Education White Nonhispanic	5.28	5.28	5.28	3.95	72.59
	(0.34)	(0.26)	(0.27)	(0.32)	(1.41)
Low Education White Nonhispanic	14.21	14.21	14.43	10.86	63.26
	(1.08)	(1.42)	(1.38)	(1.21)	(1.42)
High Education Minority	9.03	9.03	9.13	8.92	57.80
	(1.47)	(1.15)	(1.13)	(1.05)	(2.53)
Low Education Minority	18.83	18.83	19.41	15.93	48.70
	(1.73)	(1.63)	(1.56)	(1.87)	(3.03)
By Ethnicity:					
White Non-Hispanics	7.26	7.26	7.30	5.10	70.56
	(0.31)	(0.28)	(0.24)	(0.27)	(1.32)
Black Non-Hispanics	13.64	13.64	14.19	12.27	55.14
	(1.53)	(1.12)	(1.08)	(1.33)	(3.10)
Hispanics	17.30	17.30	16.88	14.25	51.87
	(2.16)	(2.02)	(1.93)	(1.77)	(2.84)
By Gender:					
Men	7.19	7.19	7.32	5.34	65.40
	(0.51)	(0.54)	(0.51)	(0.40)	(1.24)
Women	9.50	9.50	9.75	6.67	69.03
	(0.49)	(0.60)	(0.57)	(0.43)	(1.88)

Note: Table entries represent estimated coefficient of dummy for age 65 or older in models for the probability of insurance coverage (columns 1-4) or Medicare coverage (column 5). All models include quadratic in age (in quarters) fully interacted with dummy for age 65 or older. Models in columns (2)-(5) are fit to micro data: standard errors are calculated assuming a cluster structure by age.
Controls in models in columns (3)-(5) include year dummies, and dummies for gender, ethnicity, education levels, and region. Probit estimates are dummy for age 65 x density at mean. Standard errors in parentheses.

Table 4: Regression Discontinuity Estimates of Effect of Reaching Age 65 on Health Care Access and Utilization

	Delayed Care Last Year for Cost Reasons (1)	Did Not Get Care Last Year for Cost Reasons (2)	Needed to See Dr. Last Year, Didn't Because of Cost (3)	Has Usual Place for Preventative Care (4)	Saw Doctor at Least Once Last Year (5)	Spent 1 or More Nights in Hospital Last Year (6)
All	-0.56	-0.23	-2.70	1.40	0.97	1.18
	(0.64)	(0.52)	(0.56)	(0.86)	(0.68)	(0.59)
By Ethnicity/Education:						
High Education White Nonhispanic	0.31	0.21	-1.76	0.36	0.16	1.07
	(0.83)	(0.46)	(0.47)	(1.18)	(0.93)	(0.72)
Low Education White Nonhispanic	-1.12	0.20	-4.60	3.88	1.79	0.95
	(1.40)	(1.65)	(1.95)	(2.46)	(1.34)	(1.58)
High Education Minority	-1.77	-0.60	-3.54	3.74	-0.22	2.11
	(1.61)	(1.19)	(1.36)	(1.53)	(1.91)	(1.15)
Low Education Minority	-5.06	-4.39	-8.90	0.99	5.63	1.09
	(2.02)	(1.41)	(2.42)	(2.04)	(2.06)	(1.93)
By Ethnicity:						
White Non-Hispanics	0.01	0.27	-2.01	1.07	0.59	1.06
	(0.74)	(0.55)	(0.57)	(0.94)	(0.72)	(0.69)
Black Non-Hispanics	-4.17	-2.51	-5.45	4.42	2.82	1.49
	(1.82)	(1.72)	(2.07)	(1.10)	(1.64)	(1.41)
Hispanics	-5.02	-4.78	-10.21	3.35	6.35	2.56
	(1.36)	(0.99)	(3.16)	(2.29)	(2.25)	(1.95)
By Gender:						
Men	-1.17	-0.90	-1.66	1.95	0.88	2.21
	(1.03)	(0.74)	(0.63)	(1.20)	(0.85)	(0.94)
Women	0.01	0.39	-3.42	0.93	0.97	0.29
	(0.85)	(0.69)	(0.92)	(0.82)	(1.18)	(0.65)

Note: Table entries represent estimated coefficient of dummy for age 65 or older in models for outcome listed in column heading. All models fit to micro data; standard errors (in paretheses) are estimated assuming a cluster structure by age. Models include quadratic in age, fully interacted with a dummy for age 65 or older, along with sample year dummies and dummies for gender, ethnicity, region, and education levels. Models in columns (1), (2), and (4) are fit to data from pooled 1997-2001 NHIS. Models in columns (5) and (6) are fit to data from pooled 1992-2001 NHIS. Models in column (3) are fit to data from 1998-2002 BRFSS.

Table 5: Regression Discontinuity Estimates of Effect of Reaching Age 65 on Preventative Care

	Had Flu Shot in Past Year (1)	Had Blood Cholesterol Checked in Past 2 Yrs (2)	Mammogram in Past 2 Yrs (3)	Ever Had Mammogram (4)	Had PSA or Rectal Exam in Past 2 Yrs (5)	Ever Had PSA or Rectal Exam (6)	Ever Diagnosed with Hypertension (7)
All	1.03	1.45	1.02	-0.18	1.08	0.21	0.66
	(1.03)	(0.64)	(0.82)	(0.58)	(1.64)	(1.07)	(1.85)
<u>By Ethnicity/Education:</u>							
High Education	0.74	0.40	1.86	0.58	1.00	-0.01	-1.66
White Nonhispanic	(1.23)	(0.93)	(0.97)	(0.69)	(1.42)	(1.10)	(2.42)
Low Education	4.91	9.99	0.02	-2.72	-3.56	-3.43	2.78
White Nonhispanic	(1.15)	(1.74)	(2.75)	(2.15)	(5.12)	(3.43)	(3.59)
High Education	-0.32	0.57	-4.42	-2.33	4.85	3.58	9.15
Minority	(2.70)	(2.23)	(2.30)	(1.25)	(2.26)	(1.54)	(3.96)
Low Education	2.32	3.73	5.83	0.56	4.49	0.90	3.34
Minority	(3.11)	(2.31)	(2.55)	(1.43)	(5.20)	(4.37)	(5.19)
<u>By Ethnicity:</u>							
White Non-Hispanics	1.14	1.46	1.56	0.12	0.30	-0.46	-0.78
	(1.10)	(0.86)	(0.92)	(0.67)	(1.64)	(1.05)	(1.93)
Black Non-Hispanics	-2.04	-0.75	2.70	2.60	-0.71	0.29	7.93
	(2.56)	(1.74)	(2.19)	(1.57)	(3.77)	(3.51)	(4.00)
Hispanics	2.55	0.13	-3.18	-5.40	12.73	4.67	5.02
	(3.06)	(3.14)	(3.44)	(2.02)	(4.85)	(3.37)	(1.13)
<u>By Gender:</u>							
Men	-0.56	2.63	--	--	--	--	0.85
	(1.19)	(1.22)					(2.85)
Women	2.12	0.58	--	--	--	--	0.45
	(1.43)	(0.69)					(2.10)

Note: Table entries represent estimated coefficient of dummy for age 65 or older in models for outcome listed in column heading. All models fit to micro data; standard errors (in parentheses) are estimated assuming a cluster structure by age. Models include quadratic in age, fully interacted with a dummy for age 65 or older, along with sample year dummies and dummies for gender, ethnicity, region, and education levels. Models in columns (1)-(6) are fit to data from 1998-2002 BRFSS. Models in column (7) are fit to data from 1997-2001 NHIS.

Table 6: Regression Discontinuity Estimates of Medicare Eligibility on Number and Characteristics of Hospital Discharges

	California				Florida				U.S.		
	Log (No. Discharges) (x100)	Days in Hospital (x100)	Total Charges (dollars)	In-Hospital Mortality (x100)	Log (No. Discharges) (x100)	Days in Hospital (x100)	Total Charges (dollars)	In-Hospital Mortality (x100)	Log (No. Discharges) (x100)	Days in Hospital (x100)	In-Hospital Mortality (x100)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
All	6.0	-6.5	-32.3	-0.18	11.4	-15.2	-182.8	-0.32	6.4	-4.8	0.04
	(1.0)	(2.1)	(147.6)	(0.06)	(1.1)	(2.0)	(78.7)	(0.06)	(1.3)	(10.3)	(0.32)
By Ethnicity:											
White Non-Hispanic	7.1	-3.3	59.0	-0.14	13.4	-14.3	-125.0	-0.25	5.4	-20.9	-0.28
	(1.2)	(2.8)	(184.0)	(0.07)	(1.7)	(1.9)	(99.4)	(0.06)	(1.6)	(12.8)	(0.34)
Black Non-Hispanic	-0.7	-11.2	-131.0	-0.23	-0.3	-13.7	-64.7	-0.52	1.5	13.9	0.82
	(2.4)	(5.6)	(308.6)	(0.20)	(2.0)	(6.8)	(265.7)	(0.19)	(3.1)	(40.1)	(0.81)
Hispanics	5.1	-10.3	-306.2	-0.18	10.8	-17.1	-776.2	-0.43			
	(1.4)	(3.9)	(282.6)	(0.13)	(1.5)	(7.7)	(300.0)	(0.16)			
By Route into Hospital:											
Emergency Room (ER)	1.3	-14.5	-329.9	-0.16	6.0	-20.5	-481.0	-0.33			
	(0.1)	(2.7)	(194.9)	(0.08)	(1.3)	(2.4)	(143.4)	(0.10)			
Non-ER	10.8	2.2	132.9	-0.08	16.9	-9.3	-14.7	-0.20			
	(1.0)	(3.0)	(261.0)	(0.05)	(1.3)	(3.0)	(136.9)	(0.08)			
By Type of Admission:											
Elective					19.1	-15.7	-114.4	-0.12			
					(1.4)	(3.6)	(143.6)	(0.07)			
Urgent					12.8	-9.6	-225.1	-0.29			
					(1.2)	(5.7)	(215.1)	(0.09)			
Emergency					5.6	-15.6	-337.0	-0.30			
					(1.3)	(3.0)	(183.0)	(0.12)			

Note: For California and Florida, samples include people admitted to hospitals from home, discharged between 1995 and 1999 (California) or between 1995 and 2000 (Florida). Data for the U.S. come from the 1979-1999 National Hospital Discharge Survey (NHDS) Multi-Year File and are for 1995-1999. NHDS collects data on race, but not ethnicity. It also does not collect data about route into the hospital or type of admission. Models are fit to age cells, and include a quadratic for age (in years) fully interacted with a dummy for age 65 and older. Standard errors in parentheses.

Table 7: Regression Discontinuity Estimates of Medicare Eligibility on Number and Characteristics of Hospital Discharges, By Insurance Coverage Level of Non-elderly Adults in Zip Code (Florida)

	Log (No. Discharges) (x100) (1)	Days in Hospital (x100) (2)	Total Charges (dollars) (3)	In-Hospital Mortality (x100) (4)
All	11.4	-15.2	-182.8	-0.32
	(1.1)	(2.0)	(78.7)	(0.06)
<u>By Mean Fraction Uninsured in Zip Code</u>				
8.6% or Less Uninsured	12.4	-18.3	-314.0	-0.12
	(1.8)	(4.1)	(141.7)	(0.12)
8.6-11.2% Uninsured	12.0	-11.4	181.7	-0.17
	(1.6)	(3.7)	(181.7)	(0.11)
11.2-14.8% Uninsured	10.2	-16.6	-428.7	-0.47
	(1.1)	(3.3)	(157.8)	(0.10)
14.8% or More Uninsured	10.5	-21.1	-252.7	-0.44
	(1.1)	(6.0)	(241.0)	(0.14)

Note: Samples include people admitted to hospitals from home, discharged between 1995 and 2000. Models are fit to age cells, and include a quadratic for age (in years) fully interacted with a dummy for age 65 and older. Average insurance rates in zip code are computed from discharge records for people age 50 to 64. Fraction uninsured is the fraction who are coded as paying their own bill or covered by charity care or indigent care programs.

Table 8: Regression Discontinuity Estimates of Medicare Eligibility on Number of Hospital Discharges, By Admission Diagnoses and Procedures Performed in Hospital

	Log (Number of Hospital Discharges) x 100:		
	California (1)	Florida (2)	U.S. (3)
All	6.0	11.4	6.4
	(1.0)	(1.1)	(1.3)
By Admission Diagnoses:			
Chronic Ischemic Heart Disease	12.5	19.3	6.4
	(2.1)	(2.5)	(5.6)
Acute Myocardial Infarction	5.4	7.2	5.1
	(1.8)	(2.8)	(5.0)
Heart Failure	0.4	1.4	10.7
	(2.4)	(1.9)	(7.8)
Chronic Bronchitis	7.3	10.5	8.5
	(3.0)	(3.2)	(6.9)
Osteoarthrosis	15.3	34.9	14.9
	(2.7)	(3.0)	(8.0)
Pneumonia	4.3	0.8	-2.3
	(1.9)	(1.4)	(5.6)
By Procedure Performed in Hospital:			
None	4.7	9.2	8.5
	(1.3)	(1.2)	(1.6)
Diagnostic Procedures on Heart	7.4	11.3	-0.7
	(1.9)	(2.6)	(6.4)
Removal of Coronary Artery Obstruction	11.3	17.7	7.0
	(2.4)	(3.2)	(6.0)
Bypass Anastomosis of Heart	19.4	19.5	11.3
	(2.1)	(3.0)	(7.2)
Joint Replacement of Lower Extremity	14.1	30.3	7.5
	(2.2)	(2.4)	(7.1)
Diagnostic Procedures on Small Intestine	6.3	8.2	6.1
	(2.3)	(2.4)	(9.1)
Cholecystectomy (gall bladder removal)	20.4	20.7	16.4
	(2.0)	(3.4)	(6.5)

Note: See note to Table 6.

Table 9: Regression Discontinuity Estimates of Effect of Reaching Age 65 on Smoking, Exercise and Body Weight

	Smoke Daily (1)	Strenuous Exercise in Past 30 Days (2)	Overweight (3)	Obese (4)
All	0.42	-0.18	-0.53	0.86
	(0.55)	(0.49)	(0.65)	(0.59)
<u>By Ethnicity/Education:</u>				
High Education White Nonhispanic	0.83	-0.51	-0.94	0.08
	(0.63)	(0.50)	(0.89)	(0.73)
Low Education White Nonhispanic	-3.92	2.91	0.00	2.70
	(2.36)	(2.90)	(1.40)	(1.54)
High Education Minority	1.53	-0.55	-1.83	0.90
	(1.35)	(2.11)	(2.45)	(1.48)
Low Education Minority	-0.64	1.59	6.35	7.18
	(1.70)	(2.60)	(2.01)	(1.69)
<u>By Ethnicity:</u>				
White Non-Hispanics	0.31	-0.22	-0.87	0.39
	(0.78)	(0.53)	(0.74)	(0.69)
Black Non-Hispanics	0.78	-0.36	3.20	6.15
	(2.48)	(2.78)	(3.22)	(2.81)
Hispanics	-1.62	-1.39	-0.53	-0.33
	(1.23)	(2.99)	(2.55)	(2.34)
<u>By Gender:</u>				
Men	0.23	0.69	-0.09	2.09
	(0.86)	(1.03)	(0.56)	(0.64)
Women	0.52	-0.98	-0.84	-0.09
	(0.86)	(1.13)	(0.91)	(0.77)

Note: Table entries represent estimated coefficient of dummy for age 65 or older in models for outcome listed in column heading. See note to Table 4 for specification. Models are estimated using data from the 1999-2002 BRFSS.

Table 10: Regression Discontinuity Estimates of Effect of Reaching Age 65 on Self-Reported Health

	Linear Probability Model for Good or Better Health	Models for Level of Health (5 point scale 1=poor 5=excellent)	
		Linear Regression	Ordered Probit
	(1)	(2)	(3)
All	0.21	2.06	2.13
	(0.87)	(1.81)	(1.69)
By Ethnicity/Education:			
High Education White Nonhispanic	-0.34	0.59	0.83
	(0.70)	(2.07)	(2.01)
Low Education White Nonhispanic	1.96	6.81	6.17
	(2.04)	(3.60)	(3.22)
High Education Minority	-1.53	-2.00	-2.00
	(2.20)	(7.05)	(6.70)
Low Education Minority	3.97	9.93	9.49
	(2.21)	(4.92)	(4.47)
By Ethnicity:			
White Non-Hispanics	0.10	1.85	1.96
	(0.80)	(1.80)	(1.70)
Black Non-Hispanics	-0.42	2.31	2.49
	(2.50)	(7.10)	(6.70)
Hispanics	4.48	11.39	10.63
	(1.95)	(5.56)	(5.08)
By Gender:			
Men	0.94	1.80	1.66
	(1.11)	(2.27)	(2.10)
Women	-0.40	2.35	2.58
	(1.02)	(2.34)	(2.27)

Note: Table entries represent estimated coefficient of dummy for age 65 or older in models for outcome listed in column heading. Models are estimated using data from the 1992-2001 NHIS. Coefficients and standard errors in columns (2) and (3) are multiplied times 100.

Table 11: Regression Discontinuity Estimates of Effect of Medicare Eligibility on Death Rates (per 100,000 Pop) for Demographic Groups

	All (1)	Men (2)	Women (3)	Whites (4)	Blacks (5)	Hispanics (6)	White Males (7)	White Females (8)	Black Males (9)	Black Females (10)	Hispanic Males (11)	Hispanic Females (12)
Reg. Discontinuity Estimate												
Age>=65	8.76	11.23	11.04	7.13	-1.28	14.09	10.26	9.82	0.24	-1.73	17.83	11.2
	(36.82)	(53.68)	(28.58)	(34.05)	(117.42)	(24.79)	(52.46)	(25.53)	(148.50)	(102.77)	(34.63)	(25.46)
Death Rate at Age 66												
Observed	1,913	2,482	1,437	1,870	2,829	1,370	2,433	1,392	3,625	2,218	1,787	1,028
Predicted by Pre-65 Trend	1,897	2,454	1,423	1,864	2,701	1,368	2,413	1,386	3,503	2,107	1,767	1,041
Death Rate at Age 67												
Observed	2,074	2,687	1,565	2,029	3,033	1,502	2,631	1,521	4,013	2,328	1,941	1,144
Predicted by Pre-65 Trend	2,035	2,636	1,529	2,011	2,766	1,474	2,610	1,497	3,546	2,191	1,898	1,132

Note: Row labeled "Age>=65" presents estimated coefficient of dummy for age 65 or older in models for outcome listed in column heading. Models are fit to age cells and include a cubic in age fully interacted with a dummy for age 65 or older. The numerator for age-specific death rates is the number of deaths at each age registered by NCHS in the Multiple Cause of Death Files for 1989-1998 (pooled). The denominator is the postcensal estimate of the July 1 resident population of the United States at each age for 1989-1998 (pooled). Death rates are expressed per 100,000 population.

Table 12: Summary of Intergroup Variation in Reduced Form Estimates of Medicare Eligibility Effects

Outcome	Estimate of Equation (5): d_1	R^2	Gap in Outcome between Low Ed Minorities and Hi Ed Whites, Ages 63-64	Percent of Gap at Ages 63-64 Closed By Medicare Eligibility
1. Percent Delayed Care in Past Year for Cost Reasons	-0.42 (0.09)	0.76	7.0	85
2. Percent Did Not Get Care in Past Year for Cost Reasons (NHIS)	-0.37 (0.11)	0.67	7.5	70
3. Percent Did Not Get Care in Past Year for Cost Reasons (BRFSS)	-0.60 (0.12)	0.82	19.1	44
4. Percent Saw Doctor in Past Year	0.48 (0.09)	0.84	-5.5	123
5. Percent With Hospital Stay in Past Year	0.00 (0.03)	0.00	3.3	0
6. Percent With Flu Shot in Past Year	0.14 (0.19)	0.10	-13.8	14
7. Percent With Cholesterol Test in Past Two Years	0.21 (0.32)	0.08	-11.5	26
8. Percent with Mammogram in Past Two Years	0.16 (0.31)	0.05	-13.1	17
9. Percent With Prostate Exam in Past Two Years	0.35 (0.45)	0.11	-14.3	35
10. Self Assessed Level of Health (1-5 Scale)	0.77 (0.25)	0.66	-0.9	12

Notes: See text for explanation.

Appendix Table 1: Regression Discontinuity Estimates of Change in Health Insurance at Age 65, Alternative Data Sources

	NHIS: 1992-2001	NHIS: 1997-2001	BRFSS: 1998-2002
All	8.60	8.02	9.50
	(0.24)	(0.52)	(0.49)
By Ethnicity/Education:			
High Education	5.28	4.68	7.00
White Nonhispanic	(0.27)	(0.57)	(0.46)
Low Education	14.43	15.50	17.31
White Nonhispanic	(1.38)	(2.31)	(1.90)
High Education	9.13	7.27	9.78
Minority	(1.13)	(1.32)	(1.78)
Low Education	19.41	19.71	24.12
Minority	(1.56)	(2.05)	(1.73)
By Ethnicity:			
White Non-Hispanics	7.30	6.74	8.20
	(0.24)	(0.51)	(0.36)
Black Non-Hispanics	14.19	13.28	11.10
	(1.08)	(1.40)	(1.58)
Hispanics	16.88	14.31	19.01
	(1.93)	(2.36)	(3.16)
By Gender:			
Men	7.32	6.83	7.94
	(0.51)	(0.91)	(0.53)
Women	9.75	9.11	10.81
	(0.57)	(0.63)	(0.54)

Note: Table entries are estimated coefficient of dummy for age 65 or older in models for the probability of insurance coverage. All models include quadratic in age, fully interacted with dummy for age 65 or older. Models in columns (1) and (2) use age measured in quarters, for people age 55-75. Models in column (3) use age measured in years for people age 50-80. Additional controls include survey year dummies, dummies for gender, ethnicity, education levels, and region. Standard errors (in parentheses) are calculated assuming a cluster structure by age.

Appendix Table 2: Estimates of Discontinuities at Age 65 in Employment, Marriage, Family Income, and Mobility

	Microdata from 1992-2001 NHIS: Employed (1)	Cell-Level Data From 1996-2002 March CPS: Employed (2)	Married Spouse Present (3)	Family Income <$10,000 (4)	Family Income <$15,000 (5)	Family Income <$20,000 (6)	Moved to New House in Past Year (7)
All	-0.44	-1.27	-0.91	-0.42	-0.78	-0.10	-0.48
	(0.96)	(1.01)	(0.70)	(0.45)	(0.63)	(0.63)	(0.33)
By Ethnicity/Education:							
High Education	-0.78	-1.08	-1.40	-0.64	-0.68	-0.09	-0.65
White Nonhispanic	(1.34)	(1.02)	(0.76)	(0.31)	(0.48)	(0.65)	(0.32)
Low Education	0.07	-2.65	1.77	0.16	-0.35	-0.19	-0.20
White Nonhispanic	(1.71)	(1.45)	(1.91)	(1.18)	(1.82)	(1.58)	(1.02)
High Education	-2.05	-1.15	-0.04	-0.76	-1.06	-0.42	-0.30
Minority	(2.64)	(2.19)	(1.78)	(1.10)	(1.39)	(1.36)	(1.38)
Low Education	3.50	-3.89	-0.86	1.64	-1.01	0.49	-0.27
Minority	(1.63)	(2.22)	(2.40)	(1.73)	(1.92)	(2.07)	(1.73)
By Ethnicity:							
White Non-Hispanics	-0.67	-1.14	-1.00	-0.54	-0.67	-0.06	-0.53
	(1.15)	(0.98)	(0.72)	(0.37)	(0.58)	(0.61)	(0.33)
Black Non-Hispanics	1.53	0.42	-1.25	1.60	-0.60	-1.07	0.12
	(2.05)	(1.90)	(2.48)	(1.67)	(1.77)	(2.00)	(1.13)
Hispanics	0.36	-2.86	0.74	-1.85	-2.68	-1.58	1.57
	(2.87)	(2.10)	(2.63)	(1.83)	(2.43)	(2.64)	(1.56)
By Gender:							
Men	1.12	-1.07	0.52	-1.37	-2.01	-1.19	-0.77
	(1.42)	(1.74)	(1.13)	(0.61)	(0.76)	(0.60)	(0.55)
Women	-1.83	-1.65	-2.25	0.44	0.30	0.88	-0.22
	(1.14)	(0.81)	(0.83)	(0.70)	(1.00)	(0.90)	(0.50)

Note: Table entries represent estimated coefficient of dummy for age 65 or older in models for outcome listed in column heading. Models in column (1) are fit to NHIS micro data; standard errors (in paretheses) are estimated assuming a cluster structure by age. Models in columns (2)-(7) are estimated using cell level data for ages 50-79 from March 1996-2002 CPS. Models include quadratic in age, fully interacted with a dummy for age 65 or older. Models in column (1) include same controls as models in column (3) of Table 3.