Error in the Measurement of Mortality: An Application to the Analysis of Racial Mortality Disparity

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November 11, 2013

Abstract

This paper examines the nature of measurement error in the reporting of deaths in panel data sets, using the National Longitudinal Survey of Older Men (NLS-OM) as a case study. The NLS-OM collected socioeconomic data for men aged 45-59 in 1966 and in several subsequent years, and then also recorded deaths—going so far as to match with death certificate data collected in 1990. Panel data of this sort are extremely useful for examining the antecedents of mortality, e.g., studying racial differences in mortality rates. However, considerable care must be taken when analyzing such data; theoretical reasoning developed in this paper shows that the most likely forms of error in the measurement of mortality can bias estimates of the racial mortality gap. An examination of the 1990 data suggests that the match of the death certificates was less complete for blacks than for whites. In consequence, standard practice leads to an under-estimation of the black-white mortality gap. Importantly, there is now a new match of NLS-OM data to death records, and analysis of these new data confirms this finding.

Keywords: Measurement error, mortality, racial mortality disparity

This work is preliminary and incomplete. I appreciate helpful comments from Lowell Taylor, Dan Black, Seth Sanders, Daniel Nagin, Shamena Anwar, Lynne Schofield, Javaeria Qureshi, and Janna Johnson.

1 Introduction

An important body of research uses panel data for the study of mortality. This body of work seeks to provide evidence on the forces that shape mortality by following cohorts over time—examining the association between life-course factors and survival. An example is research based on the National Longitudinal Survey of Older Men (NLS-OM), a sample collected in the United States. In the NLS-OM, data were recorded for men aged 45-59 beginning in 1966 and then for several additional years up through 1983. The survey research team took considerable care to record deaths accurately. Indeed, in 1990 data were matched with death certificates from state vital records for the purpose of improving the precision of the data on deaths.

Nonetheless, as will be shown below, there is evidence that in the construction of the NLS-OM data some deaths were not recorded. In this paper I investigate the methodological and empirical issues that arise from this form of measurement error. The goals are to build intuition for the biases that likely appear if the measurement error is ignored or handled inappropriately, and see if this theoretical reasoning helps understand empirical work based on NLS-OM data. Importantly, I am able to not only use the NLS-OM matched to 1990 vital records, but also data from a recent new match.[1]

My specific focus concerns racial differences in mortality. In this respect my work parallels important earlier work by Hayward and Gorman (2004), who use the NLS-OM to study black-white differences in mortality. In that paper, the authors show that age-conditioned mortality rates are substantially higher for black men than white men, and the measured early-life social and economic conditions are responsible for only a modest amount of that gap. The Hayward and Gorman study is part of a large literature demonstrating that in the United States there are very large differences in mortality rates of black and white individuals.[2] While the proximate medical causes for the black-white gap are reasonably well known, the underlying mechanisms are not. There is ample evidence suggesting that persons of lower socioeconomic status have reduced life expectancies, but some evidence indicates that economic disparities are not the sole source of the black-white gap in mortality.[3] Sorting out the complicated roles of race and socioeconomic status is made all the more difficult by

[1]I am grateful to Professor Seth Sanders of Duke University for access to these newly matched data.

[2]For example, Harper, *et al.* (2007) note that while life expectancy at birth converged for blacks and whites during the period from 1900 to 1940, that gap remained large, and failed to decline consistently after the 1960s. Levine, *et al.* (2001) find that from 1979 to 1998 the "black:white ratio of age-adjusted, gender-specific mortality increased for all but one of nine causes of death that accounted for 83.4% of all US mortality in 1998."

[3]For example, Sorlie, *et al.* (1992) find that increased income lowers mortality rates for everyone, but that blacks have higher mortality than whites at every level of income. Guralnik, *et al.* (1993) suggest that educational attainment may have a stronger effect than race *per se* on life expectancy. More broadly, there is a large literature devoted to untangling the relationships between growth in income, improvements in nutrition, increases in education, and improvements in public health and health outcomes (morbidity and mortality). Deaton (2006) gives a valuable assessment of core issues, and Cutler, Deaton, and Lleras-Muney (2006) provide a historical overview. See also Case, *et al.* (2002), Oeppen and Vaupel (2002), and Preston (2007). Work on the black-white gap in the U.S. includes Behrman, *et al.* (1991) and Elo and Drevenstedt (2006).

the fact that conditions early in one's life are likely to influence mortality later in life. Hence the need for work that follows individuals over the life cycle is evident.

Indeed, researchers in the social sciences and public health have argued for many years that prenatal and early-childhood conditions can have important effects on mortality that stretch over the lifetime. Barker (1990 and 1995) famously argues that influences on adult health status and mortality extend back to *in utero* nutritional conditions, as it is critical for human physical development. The idea that deprivation in childhood can lead to poor health outcomes later in life has been analyzed in a great many important studies, for example, Elo and Preston's (1992) review of studies that provide evidence on the association between childhood conditions and adult mortality.[4]

In this strand of literature, some research focuses specifically on the African American population. For example, Fang, *et al.* (1996) explore the high rate of mortality from cardiovascular causes among blacks in New York City, finding that there is substantial variation among blacks based on their place of birth and that, in particular, Southern-born blacks had much higher rates of mortality from cardiovascular disease, and Caribbean-born blacks had much lower such rates, than those of their Northeastern-born counterparts. As another example, Preston, Hill, and Drevenstedt (1998) find that children who were exposed to poorer health conditions during childhood were less likely to survive to advanced ages than those living in more favorable environments, among a sample of old-age African Americans. They show that mortality risks are positively correlated across the life course, suggesting that assaults on health early in life adversely affect mortality at all subsequent ages.

In short, available evidence suggests that there is substantial value to research that uses panel data to study early-life factors that can influence later-life mortality. It is important therefore that researchers deal properly with a potential problem with longitudinal data, such as the NLS-OM—missing data on death.

Panel data sets such as the NLS-OM often rely on administrative data to record deaths. As we will see, this widely used approach is not necessarily a panacea for the problem of measurement error in death reporting. Specifically, the exploration of data quality indicates that in the NLS-OM there are a fairly large number of men who likely died for whom there was no matched death certificate data. I show that these "omitted deaths" are non-random and correlated with important covariates such as race. The error rates are especially higher for black individuals. Thus measurement error violates assumptions of classical measurement error (Fuller 1987; Carroll, Ruppert, and Stefanski 1995; Stefanski 2000; Bound, Brown, and Mathiowetz 2001; Black, Sanders, and Taylor 2003; Gustafson 2004).[5] The measurement error here is in the dependent variable and this error is correlated with the independent

[4]Research provides additional evidence see also works by Fogel (1993), Lundberg (1993), Leon, *et al.* (1998), Bengtsson and Lindström (2000), Fogel (2004), Almond (2006), Gluckman, *et al.* (2008), and Montez and Hayward (2011).

[5]Under the classical measurement error model (or errors-in-variables model), the regression model assumes that some independent variable has been measured with error. The latent true variable of interest is not directly observed. It is contaminated by the measurement error. If the measurement error is not correlated with the error terms in the regression model (i.e., it is pure random error), using the ordinary least squares (OLS) estimation, the coefficient estimates would be inconsistent and subject to attenuation bias.

variables of interest. Therefore, the well-known results of classical measurement error are not applicable.[6]

This paper develops a simple survival model that illustrates the effect of this measurement error of the sort described in the previous paragraph, showing that the estimator of the black-white mortality gap is likely under-estimated if deaths of blacks are under-reported at higher rates than deaths of whites. The empirical application shows that in the NLS-OM the mismeasurement of mortality is indeed more prevalent for blacks, and then demonstrates that improper handling of the measurement error in survival analysis causes seriously biased inference. The results of the key estimated coefficients are quite sensitive to the way the incomplete records of death are handled. As it turns out, inclusion of these omitted deaths is likely to produce correct inferences. Importantly, I am able to use new matches of the NLS-OM data to 2008 Vital Statistics. These data, which presumably has better reporting quality, confirms this prediction. Additional analysis using death reports from these new data likely provide better inference.

The paper proceeds as follows: Section 2 investigates theoretical issues of measurement error in a very simple survival model. Section 3 shows that measurement error in death is in fact an important problem in the NLS-OM data, and demonstrates that the way in which this error is handled has a significant impact on inferences one draws from the data about the black-white mortality gap. Additional analysis using the newly matched death data is provided in Section 4. Section 5 provides a discussion.

2 Measurement Error in Mortality

The goal in this section is to explore the consequences of measurement error in mortality for estimation of regression-based models of survival. The basic idea of such empirical exercises, using either cross-sectional data or longitudinal data, is simple. Data are collected for a sample of individuals (e.g., age, race, family background, etc.) who, obviously, are alive at the time data are initially collected. Subsequently, deaths are recorded for some individuals in the sample. Then regression analysis is used to examine the statistical correlates of death. The concern here is the mismeasurement of death.

The mismeasurement of death works in one of two ways—deceased individuals could be classified as being alive *or* deaths could be recorded for those who are still alive—but in many data sets most errors might will be one-sided. Consider, for example, the NLS-OM data. All men in these data were interviewed in 1966 (and most were interviewed in subsequent years). Clearly, these individuals were alive at the time data were collected. Data were

[6] One approach to solve biases induced by measurement error is to use instrumental variables (IV) estimation (Chen et al. 2007). However, for the problem pursued here, the measurement error is of a peculiar form. In particular, the error terms in the regression model are correlated with the control variable of interest. In the NLS-OM data, the error rate in the reporting of deaths is especially higher for black individuals (i.e., deaths are under-reported at higher rates for blacks). Because the measurement error is systematically correlated with the characteristics of individuals, it is possible that measurement error is positively correlated across other potential data sources of death reporting. In such case, even a second measurement of the variable of interest cannot serve as a valid IV variable because it fails the exclusion restriction assumption.

in 1990 matched with state vital records to determine dates of deaths for those who were deceased. It is virtually certain that death certificates were issued only for those who had died. The measurement error in this case is likely mostly one-sided: For some men who died the deaths may not have been matched. The focus here is this sort of mismeasurement. Extensions to include both forms of error are straightforward.

2.1 A Survival Model with Age as the Only Covariate

To set the basic idea the example starts with the simplest possible discrete survival model. Imagine that people with two ages, 0 and 1, are observed and the interest is in the impact of age on the probability of death. A common specification, which will be used here, is that the log of the death rate d_i is linearly dependent on age A_i:

$$d_i = \alpha_0 + \alpha_1 A_i + \varepsilon_i. \tag{1}$$

In estimating equation (1) $d_i = ln(D_i/n_i)$ is the dependent variable, where D_i is the number of deaths observed for individuals aged i (assuming D_i is always greater than 0) in a particular discrete time period, and n_i is the number of individuals aged i in the initial survey.

In typical empirical applications, one would also include additional covariates. (That issue will be discussed shortly.) Also, in typical applications, estimation would not proceed with OLS estimation—but instead with some more advanced procedure. Here, though, the OLS estimation is used because doing so can most easily highlight the problems that arise if measurement problems with D_i are encountered.

2.1.1 OLS Estimation with No Measurement Error

As a baseline, suppose that in fact deaths are accurately recorded in the data. Then the OLS estimator of the model's key parameter, α_1, is

$$\hat{\alpha_1} = \hat{d_1} - \hat{d_0}, \tag{2}$$

where $\hat{d_0}$ and $\hat{d_1}$ are sample log death rates at ages 0 and 1 respectively.

The OLS estimator $\hat{\alpha_1}$ is of course a consistent estimator for α_1.

2.1.2 OLS Estimation with Measurement Error, Cross-Sectional Data

The concern here is that some deaths are unrecorded. In particular suppose that proportion q_0 of deaths at age 0 are unrecorded and proportion q_1 of deaths at age 1 are unrecorded. The interest is primarily in the impact of measurement error in deaths on the OLS estimator of α_1 for two cases: cross-sectional data and longitudinal data. The example begins here with the case of cross-sectional data.

Here n_0 and n_1 people at the beginning of a period are observed and deaths recorded for the period in each age group are then observed. The observed deaths, though, are only a subset of actual deaths. In particular, $\tilde{D_0} = (1 - q_0)D_0$ deaths for young individuals and

$\tilde{D_1} = (1 - q_1)D_1$ for older individuals are observed. If observed deaths are simply treated as relevant data, it is a matter of simple algebra to verify that the OLS estimator now gives

$$\tilde{\alpha_1} = \hat{\alpha_1} + [ln(1 - q_1) - ln(1 - q_0)], \tag{3}$$

where $\hat{\alpha_1}$ is the consistent estimator from (2).

Comparison of (2) and (3) shows that in general the estimator is not consistent. The direction of the bias depends on the relationship of q_0 to q_1, and does so in an intuitive way. For example, if $q_0 > q_1$, i.e., a higher fraction of deaths among those who die at young ages is missing, then $ln(1 - q_1)$ will be smaller (in absolute value) than $ln(1 - q_0)$, and the OLS estimator, $\tilde{\alpha_1}$, is biased upward. Thus the impact of aging on death is overestimated. However, if $q_1 \cong q_0$, the estimator will not be too far off.[7]

The derivations focus here on the case in which some deaths go unrecorded, i.e., the relevant case for the empirical example below. Clearly, though, the logic also applies if the opposite pertains; the derivations allow for q_0 and q_1 to be negative (which would occur if some individuals are incorrectly recorded as deceased).

2.1.3 OLS Estimation with Measurement Error, Longitudinal Data

More interestingly, suppose the example now pertains to longitudinal data, such as the NLS-OM. In particular, the survey begins with a sample of n_0 young people. Some deaths in the first period are observed, i.e., $\tilde{D_0} = (1 - q_0)D_0$ are observed. Then in the next period some additional deaths from these same people when they are one period older are observed, i.e., $\tilde{D_1} = (1 - q_1)D_1$ are observed. Now the inference problem is more complicated; not only the number of deaths is mismeasured, but the number of older individuals (i.e., n_1) that is used as the denominator of the death rate among those aged 1 is also mismeasured.

It is a matter of simple algebra to show that the OLS estimator for this case is now

$$\check{\alpha}_1 = \hat{\alpha_1} + \left[ln(1 - q_1) - ln(1 - q_0) + ln\left(\frac{n_1}{n_1 + q_0 D_0}\right)\right], \tag{4}$$

where again $\hat{\alpha_1}$ is the consistent estimate from (2). Notice that in this case, even if the error rates in reporting deaths are the same for those aged 0 and 1, the estimator is inconsistent. With longitudinal data, when $q_1 \cong q_0$, the estimator is biased downward since the last term in equation (4) is negative. This source of bias will be quite small (in absolute value) if the number of deaths among the young (D_0) is small relative to the number surviving to the older age (n_1), but will be more substantial in a population with a higher death rate among the young.

[7] In this latter case, though, the OLS estimator of α_0—the baseline mortality rate—will be inconsistent. For some applications this parameter may be of less interest.

2.2 A Survival Model with Two Covariates, Age and Race

Suppose now the model has two covariates —"age" and "race" in the example. In particular, suppose

$$d_i = \alpha_0 + \alpha_1 A_i + \alpha_2 B_i + \varepsilon_i, \tag{5}$$

where the additional covariate, B_i, is a race indicator,

$$B_i = \begin{cases} 1 & \text{if the respondent is black, and} \\ 0 & \text{if he is white.} \end{cases} \tag{6}$$

Now let $n_0 = n_0^B + n_0^W$ be the number of individuals aged 0 in the samples, with n_0^B indicating the number of blacks and n_0^W indicating the number of whites. Analogous notation is used for those aged 1, $n_1 = n_1^B + n_1^W$.

2.2.1 OLS Estimation with No Measurement Error

With a bit of algebra one can verify that the OLS estimator of the age coefficient α_1 is the weighted sum, for blacks and whites respectively, of the differences between the mean log death rates of the old and the young. Specifically

$$\hat{\alpha_1} = \phi(\hat{d}_1^B - \hat{d}_0^B) + (1-\phi)(\hat{d}_1^W - \hat{d}_0^W), \tag{7}$$

with the weight ϕ given by the surprisingly involved expression,

$$\phi = \frac{(n_0^W + n_1^W)^2 + n_0^B(2n_0^B + n_0^W) + n_1^B(2n_1^B - n_0^W) + n_1^W(n_1^B - n_0^B)}{(n_0^B + n_0^W)^2 + (n_0^B + n_1^B)^2 + (n_0^B - n_1^W)^2 + (n_0^W + n_1^W)^2 + (n_1^B + n_1^W)^2 + (n_0^W - n_1^B)^2}.$$

Similarly, the race coefficient is the weighted sum of the difference between the log death rate of blacks and whites for those aged 0 and the difference between the log death rate of blacks and whites aged 1:

$$\hat{\alpha_2} = \theta(\hat{d}_0^B - \hat{d}_0^W) + (1-\theta)(\hat{d}_1^B - \hat{d}_1^W), \tag{8}$$

with

$$\theta = \frac{(n_1^B + n_1^W)^2 + n_0^B(2n_0^B + n_1^B) + n_0^W(2n_0^W - n_1^B) + n_1^W(n_0^W - n_0^B)}{(n_0^B + n_0^W)^2 + (n_0^B + n_1^B)^2 + (n_0^B - n_1^W)^2 + (n_0^W + n_1^W)^2 + (n_1^B + n_1^W)^2 + (n_0^W - n_1^B)^2}.$$

These estimators are consistent.

2.2.2 OLS Estimation with Measurement Error, Cross-Sectional Data

As above, the interest is in the impact on the estimators of measurement error in death rates. Let q_0^B be the fraction of deaths that go unreported for blacks aged 0, and define q_0^W, q_1^B, and q_1^W analogously. Generally in the analytical cases these are positive (i.e., deaths are under-reported), though nothing in the derivations is changed if they are negative (i.e., if deaths are over-reported).

Suppose again that we are working with a cross-sectional data set in which initial samples of n_0^B and n_1^B blacks and n_0^W and n_1^W whites aged 0 and 1 are observed at the beginning of a period, and then deaths in each period are observed. With a bit of algebra one can show that impact of measurement error in deaths is quite intuitive:

$$\tilde{\alpha_1} = \hat{\alpha_1} + \phi[ln(1-q_1^B) - ln(1-q_0^B)] + (1-\phi)[ln(1-q_1^W) - ln(1-q_0^W)], \tag{9}$$

and

$$\tilde{\alpha_2} = \hat{\alpha_2} + \theta[ln(1-q_0^B) - ln(1-q_0^W)] + (1-\theta)[ln(1-q_1^B) - ln(1-q_1^W)], \tag{10}$$

where $\hat{\alpha_1}$ and $\hat{\alpha_2}$ are the consistent estimators given in (7) and (8) respectively.

Equations (9) and (10) provide useful insight into how measurement error is likely to affect the estimates.

First, if the measurement error is similar for these four age-race groups, $q_0^B \cong q_1^B \cong q_0^W \cong q_1^W$, the OLS estimators will be close to consistent.[8]

Second, the observations about bias to the age coefficient from Subsection 2.1.2 carry over here. For instance, if for both blacks and whites deaths are under-reported at higher rates for the young than the old, i.e., if $q_0^B > q_1^B$ and $q_0^W > q_1^W$, then the OLS estimator of α_1 will be biased upward. If, on the other hand, deaths are under-reported at higher rates for the old, the estimator will be biased downward.

Third, it is easy to see how bias might be generated in the race coefficient, $\tilde{\alpha_2}$. Below it will be shown that in the death certificate data matched to the NLS-OM, deaths are under-reported at highest rates for blacks. Suppose, therefore, that $q_0^B > q_0^W$ and $q_1^B > q_1^W$. Clearly, from (10), one can see that the consequence will be that $\tilde{\alpha_2}$ will be biased downward. That is, the black-white mortality gap is under-estimated.

2.2.3 OLS Estimation with Measurement Error, Longitudinal Data

The example next turns to the more interesting case of longitudinal data. In particular, suppose that now a cohort of n_0^B black individuals and n_0^W white individuals are followed over two periods, and those data are used to estimate the model.

After extensive algebraic manipulation, one can show now the OLS estimator of the age coefficient is

$$\begin{aligned} \tilde{\alpha}_1 \;=\; & \left\{\tilde{\phi}(\hat{d}_1^B - \hat{d}_0^B) + (1-\tilde{\phi})(\hat{d}_1^W - \hat{d}_0^W)\right\} + \\ & \left\{\tilde{\phi}[ln(1-q_1^B) - ln(1-q_0^B)] + (1-\tilde{\phi})[ln(1-q_1^W) - ln(1-q_0^W)]\right\} + \\ & \left\{\tilde{\phi}\left[ln\left(\frac{n_1^B}{n_1^B + q_0^B D_0^B}\right)\right] + (1-\tilde{\phi})\left[ln\left(\frac{n_1^W}{n_1^W + q_0^W D_0^W}\right)\right]\right\}, \end{aligned} \tag{11}$$

with weights constructed using

$$\tilde{\phi} = \frac{\begin{array}{c}[(n_0^W + n_1^W)^2 + n_0^B(2n_0^B + n_0^W) + n_1^B(2n_1^B - n_0^W) + n_1^W(n_1^B - n_0^B)] + \\ \{[(4n_1^B - n_0^W + n_1^W)q_0^B D_0^B + (-n_0^B + n_1^B + 2n_0^W + 2n_1^W)q_0^W D_0^W] + [2(q_0^B D_0^B)^2 + (q_0^B D_0^B)(q_0^W D_0^W) + (q_0^W D_0^W)^2]\}\end{array}}{\begin{array}{c}[(n_0^B + n_0^W)^2 + (n_0^B + n_1^B)^2 + (n_0^B - n_1^W)^2 + (n_0^W + n_1^W)^2 + (n_1^B + n_1^W)^2 + (n_0^W - n_1^B)^2] + \\ \{2(n_0^B + 3n_1^B - n_0^W + n_1^W)q_0^B D_0^B + 2(-n_0^B + n_1^B + n_0^W + 3n_1^W)q_0^W D_0^W + [3(q_0^B D_0^B)^2 + 2(q_0^B D_0^B)(q_0^W D_0^W) + 3(q_0^W D_0^W)^2]\}\end{array}}.$$

[8] The estimator of the intercept in the regression $\tilde{\alpha_0}$ will typically be inconsistent, but as noted above, that parameter might be of less interest.

Three terms in curly brackets on the right hand side of (11) are relatively easy to interpret:

The first term is very similar to the OLS estimator (7). The difference is that the weights have now changed. This expression is thus a consistent, but not efficient, estimator of α_1.

The second term introduce bias in roughly the same way in cross-sectional data, as shown in (9). The only difference is that the weights differ. So if, for example, error rates are similar for old and young individuals in the sample (for both races), $q_0^B \cong q_1^B$ and $q_0^W \cong q_1^W$, then this source of bias will be close to zero.

The third term appears for the following reason: If some deaths at age 0 are missing, this will cause overestimation of the base for calculating the death rate at age 1. This in turn causes underestimation for mortality at age 1; this third term is negative. As in the simpler case above, the source of bias will be quite small (in absolute value) if deaths at age 0 (D_0^B and D_0^W) are infrequent relative to the number of survivors (n_1^B and n_1^W).

As for the coefficient on race, α_2, one can show that the OLS estimator here is

$$\begin{aligned}
\breve{\alpha}_2 \;=\; & \left\{\tilde{\theta}(\hat{d}_0^B - \hat{d}_0^W) + (1-\tilde{\theta})(\hat{d}_1^B - \hat{d}_1^W)\right\} + \\
& \left\{\tilde{\theta}[ln(1-q_0^B) - ln(1-q_0^W)] + (1-\tilde{\theta})[ln(1-q_1^B) - ln(1-q_1^W)]\right\} + \\
& \left\{(1-\tilde{\theta})\left[ln\left(\frac{n_1^B}{n_1^B + q_0^B D_0^B}\right) - ln\left(\frac{n_1^W}{n_1^W + q_0^W D_0^W}\right)\right]\right\}, \qquad (12)
\end{aligned}$$

with weights constructed using

$$\tilde{\theta} = \frac{\begin{array}{c}[(n_1^B + n_1^W)^2 + n_0^B(2n_0^B + n_1^B) + n_0^W(2n_0^W - n_1^B) + n_1^W(n_0^W - n_0^B)] + \\ \{[(n_0^B + 2n_1^B - n_0^W + 2n_1^W)q_0^B D_0^B + (-n_0^B + 2n_1^B + n_0^W + 2n_1^W)q_0^W D_0^W)] + (q_0^B D_0^B + q_0^W D_0^W)^2\}\end{array}}{\begin{array}{c}[(n_0^B + n_0^W)^2 + (n_0^B + n_1^B)^2 + (n_0^B - n_1^W)^2 + (n_0^W + n_1^W)^2 + (n_1^B + n_1^W)^2 + (n_0^W - n_1^B)^2] + \\ \{2(n_0^B + 3n_1^B - n_0^W + n_1^W)q_0^B D_0^B + 2(-n_0^B + n_1^B + n_0^W + 3n_1^W)q_0^W D_0^W + [3(q_0^B D_0^B)^2 + 2(q_0^B D_0^B)(q_0^W D_0^W) + 3(q_0^W D_0^W)^2]\}\end{array}}.$$

Again there are three terms in curly brackets to be interpreted:

The first term is similar to the OLS estimator (8), but with different weights. This term is a consistent, but inefficient, estimator of α_2.

The second term is similar to bias identified in the cross-sectional case, as shown in (10). As mentioned above, in the empirical example below mismeasurement is a bigger problem for blacks than for whites, i.e., $q_0^B > q_0^W$ and $q_1^B > q_1^W$. For such a situation this second term is clearly negative; this biases the OLS estimator of the black-white mortality gap downward.

The third term has an ambiguous sign, as each expression within the square bracket is negative. One can see what happens in some special cases. For instance, if there is measurement error for blacks but not whites, $q_0^B > 0$ and $q_0^W = 0$, the entire term is negative. One thus expects more generally that the entire term is negative as long as the measurement error for blacks is sufficiently larger than the measurement error for whites. Also, notice that the term is more likely to be negative when D_0^B is large relative to D_0^W. Importantly, since the weights in the expression depend on $\tilde{\theta}$, the composition of the population (e.g., the proportion black) affects the size of this bias. As above, the size of this bias will be small (in absolute value) if the number of deaths (D_0^B and D_0^W) are infrequent relative to the number of survivors (n_1^B and n_1^W).

From this brief theoretical discussion, it is clear that the measurement error in mortality has a potentially significant impact on the statistical inference about racial disparity in mortality. In particular, in panel data, if deaths are under-reported at higher rates for the young than the old, then the estimator of the age coefficient will be biased upward. If deaths for blacks are under-reported at the highest rates, the black-white mortality gap is likely under-estimated. Below it will be shown that the empirical examination using the NLS-OM data agrees well with the model's predictions about the nature of the bias of the key coefficients.

3 An Empirical Example Using the NLS-OM

3.1 The National Longitudinal Survey of Older Men

The National Longitudinal Surveys (NLS) are a series of surveys established to collect important information on labor market activities and other significant life events at various points in life for several groups of people. One of these surveys, the National Longitudinal Survey of Older Men (NLS-OM) has proved to be an important source of research in social science, including the analysis of the role of race and socioeconomic status on mortality. Indeed, a number of recent papers use these data for that purpose, including Hayward, *et al.* (1997), Hayward and Gorman (2004), and Warner and Hayward (2006).

The NLS-OM first interviewed 5020 respondents in 1966. The age eligibility was men 45 to 59 on April 1, 1966. Thus, the survey covers birth cohorts from 1906 through 1921. The NLS Older Men then were interviewed a further 12 times from 1967 to 1983. In 1990, the last interview was completed by living respondents or by the widows or other family members of deceased respondents. At that time, the oldest cohorts in the NLS-OM were aged 80 or older, and there was therefore substantial mortality; mortality rate could be inferred up through fairly old ages for these men. As of the last date of data collection, it appears that 53.3% of Older Men were deceased.

Importantly, for the work that follows, the NLS Older Men survey reported a total of 2674 deaths from 1966 to 1990 for mortality in two ways. First, the 1990 data were matched with death certificates from state vital records to record deaths. Second, throughout the data collection process—up through 1983 and again in 1990—there are life status reports by the survey or by widows (or relatives) that can be used to infer death.[9]

Before turning to an analysis of mortality and the correlates of mortality, basic statistics about the socio-economic characteristics of the men in the sample are reported in Tables 1 and 2. As children, NLS Older Men generally lived in households in which the heads had low levels of education. Most report living with biological parents during childhood. For the most part, NLS Older Men grew up in rural communities. Many lived in towns with fewer than 25,000 people or lived in rural farm areas. Compared to their parents, average years of education improved, but educational attainment is low relative to present averages. As adults, these men were much more likely to live in or near urban areas than as children.

[9] The reports by widows or relatives in the last interview provide age of respondent at death.

The data included some lifestyle measures, including alcohol consumption (which is quite low among those who provide reports), smoking, and the body mass index (BMI), which can be used to assess the subsequent impact of obesity on mortality.[10]

3.2 Initial Regression Analysis Using Vital Record, 1966–1983

The primary interest here concerns statistical inference about the role of race as a correlate of mortality in the sample of NLS Older Men. As mentioned above, such analysis has already been undertaken, most notably in the important work of Hayward and Gorman (2004). I revisit this analysis because I hope to understand the role of measurement error in mortality as discussed above.

As has been noted, in the NLS-OM data, death can be recorded in one of two ways: by death certificates from state vital records or by an indication that data went unrecorded because the respondent was deceased.

I begin here by undertaking regression analysis of mortality using the entire sample over the 1966-1983 period, and taking the "conservative" approach of treating each respondent as alive unless a death is recorded by death certificate. Notice that in taking this approach I am replicating the analysis that a researcher would undertake who had an initial sample of individuals who were known to be alive at a point in time (in the current case 1966) and then had access to official records that recorded deaths for that sample. To the extent that there are deaths for which death certificates are *not* successfully matched to the original data, deaths will be under-reported using this approach.

For the first set of analyses, I restrict attention to the period 1966 through 1983. The reason for focusing on this period is over this span, regular data collection continued for the NLS-OM cohorts. Thus for this period I can draw some reasonable inferences about the consequences of taking the "conservative" approach of using Vital Statistics as a means of recording deaths.

The basic regression approach follows Warner and Hayward's (2006) paper, "Early-Life Origins of the Race Gap in Men's Mortality." In that paper, the authors conduct survival analysis (also called "event-history analysis") in which a series of discrete-time hazard models are estimated for the purpose of evaluating the ways in which social and economic conditions in childhood are associated with mortality. The specific goal is to see how those early-life conditions contribute to the race gap in men's mortality.[11] Their analysis is conducted by estimating a series of models that regress the risk of mortality on each of several sets of early-life conditions separately. Through the changes in the coefficients across models, one can potentially assess the life-course pathways that account for the race gap in mortality. The authors argue that early-life conditions indirectly affect the race gap in mortality via adult socioeconomic status.

[10] These results are similar to those reported by Hayward and Gorman (2004) and Warner and Hayward (2006).

[11] See also Allison (1984), Hayward and Gorman (2004), and Hosmer, Lemeshow, and May (2008).

For the regression models,

$$h(a) = \lim_{n \to 0} \frac{P(a+n>T \geq a|T \geq a)}{n} \tag{13}$$

gives the force of mortality at exact age a, given that a person has survived to that age. The basic association between mortality risk and age is then assumed to follow the log-linear model that I employed above

$$lnh(a) = \beta_0 + \beta_1 A, \tag{14}$$

where A is the age of a person at his previous birthday. The series of nested models are Model 1:

$$lnh(a) = \beta_0 + \beta_1 A + \gamma_i CHILD_i, \tag{15}$$

where $CHILD$ represents a key set of characteristics established in childhood—race, five-year birth cohort, and being foreign-born—that are included in every regression. Then Model 2 is

$$lnh(a) = \beta_0 + \beta_1 A + \gamma_i CHILD_i + \beta_2 EDUC_i, \tag{16}$$

where $EDUC$ represents education of head of household when that respondent was a child; Model 3 is

$$lnh(a) = \beta_0 + \beta_1 A + \gamma_i CHILD_i + \beta_2 FAMILY_i, \tag{17}$$

where $FAMILY$ is a vector that represents family structure; and Model 4 is

$$lnh(a) = \beta_0 + \beta_1 A + \gamma_i CHILD_i + \beta_2 COMM_i, \tag{18}$$

where $COMM$ represents community characteristics.

The first model is the "baseline model" which gives the main effect of age and race on mortality. Then the intention of the analysis is to assess whether parental education ($EDUC$), family structure ($FAMILY$), and community characteristics ($COMM$) in childhood affect the magnitude of the key parameter estimates.

The full sample of 5020 is used for this analysis, excluding a small number of cases for which data are missing on independent variables.[12] The results of the analyses are given, in full, in the appendix (see Appendix Tables A).[13] The interest here is primarily on the coefficients on age and race, so a truncated version of the results are presented in Panel A of Table 3. As expected, the log force of mortality is increasing in age. Also, as expected, conditional on age (and cohort of birth and foreign-born status) the force of mortality is substantially higher for blacks than for whites. It is also found that the estimated effect of race on mortality is not substantially altered by inclusion of other measured individual-level characteristics.

[12]Thus, for example, data on age, cohort, foreign-born status and/or race are missing on 48 individuals, which gives a final sample size of $n = 4972$ for Model 1.

[13]The estimated coefficients, instead of the hazard ratios, are reported in the tables.

3.3 Regression Analysis Using Deaths Reported in the NLS, 1966–1983

As has been noted, use of vital records to record deaths is a very conservative approach here, and is likely to lead to under-reporting of deaths. As shown above, this sort of mis-measurement can create bias in parameter estimates, especially if the unrecorded deaths are systematically related to characteristics of individuals in the sample.

To see how this might matter here, I repeat the regression analysis, but now I include not only deaths that are recorded in vital records, but also those that appear in the NLS data collection process. Thus, for example, for many records, data are missing for a particular year (and all subsequent years) and the recorded reason is that the respondent is deceased. For a large number of such cases, the respondent also has a death recorded via death certificate. For some cases, though, these deaths were not recorded in the Vital Statistics. I ask what happens if these cases are included.[14]

Results are reported in Panel B of Table 3.[15] The differences between Panel A and Panel B are striking. It is noticed that if using the death certificates to record deaths, the age coefficient is substantially *over-estimated* and the race coefficient is substantially *under-estimated*. The theoretical results from the previous section provide guidance about how this problem arises. (Panel C is presented for future reference and is discussed below.)

The data used to estimate the key regressions are certainly "panel data"; identification of the parameters comes in part from the longitudinal component (as measured mortality changes as cohorts age) and from the cross-section (as measured mortality varies in the cross-section for men of different ages). Thus the lessons from the longitudinal analysis and the cross-sectional analysis pertain. Fortunately, those lessons are very similar, as can be seen from comparing results in (9) and (10) with results in (11) and (12). In particular,

[14] The age at death reported by the widows or proxy of the respondents in the 1990 survey is used for analysis for these cases.

[15] The regressions given in Panel B of Table 3 include as "deaths" (1) those deaths that are recorded by death certificates *and* (2) those deaths that appear also as recorded deaths in the NLS-OM survey. It is worth noting that for a few of these cases the age at death in vital records does not line up with the reports in the NLS-OM. For these inconsistent cases, further adjustments on their timing of death are made in the analyses. Among those cases that death certificates and NLS-OM reports both confirm that they were alive before 1983 (though it is still likely that they could die in between 1983 and 1990), 133 individuals whose age at death in death certificates show that they died before 1983 are, therefore, treated as dead before 1983 in the regressions. Also among this double-confirmed alive group, 80 individuals are recorded as dead after the year of their last interview (1990) according to death certificates; they are assumed to be alive until 1990.

On the other hand, among those cases who are twice confirmed dead before 1983 from NLS-OM and death certificates, 7 respondents whom are recorded as dead before the year of first interview (1966) from death certificates consequently are treated as dead in 1967 in the regressions. Among the same double-confirmed dead group, 54 respondents whom are reported dead between 1983 and 1990 from death certificates are then treated as alive before 1983 and dead between 1983 and 1990 in the analyses. Also, within this group, there is one case reported dead after 1990 according to death certificates; he is treated as dead in 1990.

It is suspected that most of the deaths that show up in NLS-OM data are in fact deaths, as it is difficult to see why widows or other surviving relatives would mis-report this. In any event, while it is possible that some of these cases are reported deaths for individuals who are in fact alive, it seems that the results would be much closer to actual outcomes if including these cases.

the nature of the bias of the key coefficients is related to the extent to which the individual characteristics of people with omitted deaths differ from those with recorded deaths.

3.4 Characteristics of Individuals with Likely Deaths *Not* Recorded in Vital Records

To repeat the key point from the analysis in the previous section, the omission of death records is likely to be particularly problematic if the characteristics of those whose deaths are unrecorded differ from the characteristics of those whose deaths are recorded. With this in mind, consider Table 4. This table gives average characteristics for two groups—those who had deaths recorded in the vital records and matched to the NLS-OM data, and those who had deaths as indicated in the NLS *but not in the death certificate data from state vital records.* This latter group of 382 men are those that would be omitted from an analysis based on death certificate data.

Some striking results are observed when comparing these two groups. First, the death ages recorded in NLS-OM (collected directly from the widows or proxy of the respondents) indicate that the group of 382 men died at relatively young ages. Their average death age is 62.02, while it is 62.95 for the other group. Among blacks, the 382 men seem to have died at younger ages. The average death age of blacks is about 61.55 for the 382 men, while the average death age of blacks is about 62.88 in the other group. Second, this group of 382 men is disproportionately black. It is found that the proportion of blacks in the 382 men is larger than the proportion of blacks in the other group. Of the 382 men, 16.22% are black, while only 10.54% are black in the other group. The above comparisons raise the concern that the unrecorded deaths differ systematically across groups. Thus, the empirical evaluation of black-white mortality gap should account for the presence of measurement errors. Since the data fail to record deaths for those more likely to be black and young at death age, the age coefficients are over-estimated and the race coefficients are under-estimated. The differences in the age and race estimates between Panels A and B in Table 3 are mostly likely due to the systematically unreported deaths.

3.5 Regression Results Using Consistent Records Only

The omission of deaths that go unreported in the death certificate data from regression analyses give results that differ substantially from those that include such deaths. As has been noted, though, some problems remain. I cannot know for certain, for example, that deaths that have no death certificates did actually occur. Also, there are cases in which the death ages do not line up from the two data sources.

One way of dealing with these inconsistencies is to use only data with consistent records. In empirical work generally researchers often discard data for which records are incomplete or inconsistent. Here I can follow in that tradition by doing the same for records for which death records and ages fail to match up consistently.[16]

[16]By following this path, the analysis seems to roughly follow Hayward and Gorman (2004) and Warner

Results of this exercise are reported in Panel C of Table 3. The most important point to make with this set of results is that the key estimated coefficients are in between those found in Panel A and those found in Panel B.

The interpretation is as follows: As noted above, the Panel A estimates are deeply flawed because a substantial number of deaths are going unreported, and moreover because the characteristics of men with unreported deaths differ substantially from those with reported deaths. In particular, it has been shown that those with unreported deaths are more likely to be black and young at age of death. It is suspected that the results in Panel B are likely to be more accurate.

Now the sample used to produce the results reported in Panel C excludes a number of cases that seem "problematic," but in so doing once again excludes a large number of deaths that almost certainly occurred, and as has just been emphasized the excluded cases are disproportionately deaths of those who are black and young at age of death. At least in the data used for Panel C those cases are not treated as individuals who survived throughout the period. Still, as an empirical matter, simply excluding those cases is almost as bad as coding them as survivors. It appears that doing so leads to inconsistent estimates of the key parameters.

3.6 Regression Results Using Data 1966-1990

In the analyses just reported, the data used is only up through 1983. By using data for this period, I can identify a number of likely deaths that are *not* recorded in the death certificate data, because regular interviews on the men were being conducted. This allows me further to see how inferences differ if I (properly) include those as deaths or (improperly) simply exclude those cases from analysis.

Previous research uses these data up through 1990, which is clearly advantageous because this allows for the inclusion of deaths at older ages. The basic measurement issues still likely pertain for these years, but I do not have regularly-collected data with which to examine the problem. What I do have, though, is an additional report in 1990 in which data were again collected from men who were alive or from widows or other relatives for those who were deceased.

Thus I can repeat the regression analyses, again treating death records in three different ways. First, I can rely on death certificate records only. Second, I can include deaths reported on death certificates *and* other deaths reported in the NLS-OM. Third, I can simply exclude all cases with inconsistent records. Given the discussion above, I suspect the second of these options is likely to produce correct inferences.

With this in mind, consider results reported in Table 5. The basic pattern is similar to that reported in Table 3. Most importantly, compare results in Panels B and C. If inconsistent records are excluded, it is likely to under-estimate the impact of race on mortality and over-estimate (by a small amount) the impact of age on the force of mortality.[17]

and Hayward (2006).

[17] When comparing the results from Table 5 to the results from Warner and Hayward's (2006) paper, it

4 Additional Analysis Using Vital Record, 2008

Importantly, a new match has recently been conducted for the NLS-OM data. This new match is with state vital records collected in 2008 (hereafter referred to as "2008 VS"). I can thus use these new data to assess the accuracy of death data recorded by the Census Bureau in 1990 (henceforth referred to as "1990 VS"). Recall that in the 1990 NLS survey, death records come from a match with death certificates from state vital records for those the Census Bureau believed to be deceased. As we have seen, in some cases the death records were not successfully matched. Moreover, with previously available data we cannot be sure about purported deaths for which there is no death certificate. The 2008 VS match provides a great opportunity to check once again deaths recorded in the NLS-OM data.

As of 2008, surviving Older Men would have been aged approximately 87 to 101 years old. Most Older Men were thus likely to have died. Thus it is not surprising that in the newly matched data, 92.85% of Older Men are found to be deceased. By matching the data once again to vital records it is now possible to determine the age of death for almost every one of these deaths. Importantly, the 2008 VS collected death records were matched with Social Security numbers and Numident files from the Vital Statistics data. Thus the quality of the 2008 VS match is likely to be much better than in 1990 VS (if only because of better matching algorithms now available). One would expect the number of cases with missing death or mismatched age of death to be relatively low. In short, the 2008 VS is likely to provide lower measurement error.

The goal here, therefore, is to use 2008 VS to check the accuracy of deaths that are recorded in the 1990 VS. I can see who was missed in the death records from 1990 VS, and presumably can also find some individuals incorrectly recorded as deceased (who in fact should have been classified as alive).

Table 6 compares the reporting of deaths among the data sources. First consider Panel A, which compares individual death records as matched to 1990 Vital Statistics and then as matched to the 2008 Vital Statistics. The first three rows show cases for which one or both sources are in error. Assuming that the match to 2008 records is correct, we find 609 "false negatives" (cases in which a death was *not* recorded in the 1990 data), compared to only 42 "false positives" (cases in which a death was erroneously recorded). Clearly, the measurement error is heavily dominated by the first sort of error (as assumed in the discussion above). The most common cases of error, false negatives, tend to be men who die at relatively young ages (age 66.05, compared to age 67.88 for deaths that were correctly matched in the 1990 VS), and who were disproportionately black (14%, compared to 9% among the correct matches). This is exactly the problem highlighted above.

As for deaths recorded in the 1990 NLS report (henceafter referred to as "1990 NLS") more generally, Panel B shows that measurement error overall is much lower. Even so,

seems that the estimates given in Panel C are most comparable to their results. It appears that the sample excluding all cases with inconsistent records is likely to be the most comparable one to the sample analyzed in their paper, although the impact of race would be under-estimated and the impact of age would be over-estimated on mortality when using this sample. The slight disagreements between our results imply that we are not using the same samples since their scheme used to deal with the unrecorded deaths is still unknown.

1990 NLS does have appears to have some error—48 false negatives, 42 false positives, and 98 cases in which the age of death was misreported. All three of these error types are disproportionately common among blacks.

4.1 Comparing Mortality Estimates from the NLS-OM with Other Sources

It seems likely, as noted above, that the 1990 VS NLS-OM match is much less accurate than the 2008 VS NLS-OM match and the NLS-OM data more generally. It is possible to provide evidence on this conjecture by comparing mortality estimates from these sources with independent estimates derived using data from U.S. Census and Vital Statistics records.

To conduct this exercise I form estimates of ten-year death rates from 1980 through 1990 in four different ways—using NLS-OM records in the three ways described above (1990 NLS, 1990 VS, and 2008 VS) and then also using U.S. Decennial Census samples and Vital Statistics data to form a baseline comparison. My approach for this last estimate follows Black, Hsu, Sanders, and Taylor (2012).[18]

What is needed here to form the baseline comparison is an estimate of $d_i^{1980-1990} = \frac{D_i^{1980-1990}}{N_i^{1980}}$, where i indexes the demographic group in question, i.e., the birth cohort by race. I proceed by assuming that the Vital Statistics data provide an accurate count of D_i. Then I use a GMM approach to give me estimates of N_i^{1980}. This procedure is described in detail in Appendix D. The procedure efficiently combines data from the 1980 and 1990 5 percent public use samples of the U.S. Census and annual 1980-1990 detailed mortality files from the U.S. Vital Statistics. I thereby estimate N_i^{1980} for men born in years 1906 through 1921.[19] The 1980-1990 ten-year death rate estimates are then calculated, $d_i^{1980-1990} = \frac{D_i^{1980-1990}}{N_i^{1980}}$, with the denominator estimated by the GMM approach.

Figure 1 gives the ten-year mortality rates, 1980-1990, for Older Men under study (birth cohorts 1906-1921). Figures 2 and 3 give the death rates separately for black and white men. The ten-year mortality estimates are quite noisy with all NLS-OM approaches, especially for the relatively smaller black cohorts. In Figure 1, it appears that the 2008 VS and the 1990 NLS estimates are very close to one another for most cohorts. This suggests that these two have very similar quality of reporting for deaths. As it turns out, the death records from 1990 VS under-report the mortality rates for most of these cohorts. In all figures, the GMM estimates give quite smooth mortality curves. As expected, it appears that the death rates from 1990 NLS and 2008 VS are much closer to the GMM baseline formed from Census and Vital Statistics data than are death rates estimated using the 1990 VS.

[18] I use estimates of ten-year mortality, 1980-1990, for my comparison because they provide much smoother mortality estimates.

[19] I estimate mortality for birth cohort 1906-1921 as I did for the NLS Older Men samples.

4.2 Regression Analysis Using Vital Records, 2008

The purpose of my final piece of analysis is to revisit regressions from Section 3 to see how inferences about the racial mortality gap differ if I use the deaths reported in 2008 VS for analysis. For some of regressions I use data only up through 1990, as a way of comparing results with the 1990 VS. In addition, I can now try regressions that include deaths at older ages.[20]

To begin, in Table 7 I report the results from regressions using the 1990 VS and the 2008 VS. The deceased status information is obtained from these data up through 1990 (regressions similar to the analysis in Panel A of Table 5). Here the age coefficient appears to be larger and the race coefficient appears to be smaller in Panel A than in Panel B. This analysis again confirms that serious biases arise from the measurement error that appears in the 1990 VS data.

I next repeat the analysis in Panel A of Table 7, treating death records in different ways. First, I exclude cases with inconsistent records between 1990 VS and 2008 VS. Second, I include deaths reported in the 2008 VS that were known to be deaths before 1990 (i.e., false negative cases in 1990 VS). Third, I correct for cases that have age of death mismatched in the 1990 VS and 2008 VS. Age at death reported in the 2008 VS is used for these mismatched cases. Fourth, I adjust for the false positive cases in 1990 VS, treating them as alive according to the reports from 2008 VS. Lastly, I correct for all mismeasured cases (false negative, death age mismatched, false positive) between these two data, using deaths reported in the 2008 VS as the basis.[21] Results are reported in Table 8. Panel A of Table 8 suggests that excluding inconsistencies does *not* help to reduce bias in parameter estimates. Note that this is the same conclusion that was drawn in Section 3.5. It is clear that such an approach biases the race coefficient towards zero. Results in Panel B of Table 8 suggest a similar conclusion to that found in Section 3.3. The differences in Panel A of Table 7 and Panel B of Table 8 shows that when omitting deaths for those who are more likely to be black and die at young ages in the analyses, the age estimates are likely over-estimated (by a small amount) and the race estimates are likely under-estimated. Panels C and D of Table 8 correct bias in the age and race coefficients slightly. Results in Panel E of Table 8 are quite close to those found in Panel B of Table 7.

Next, I repeat the analysis in Panel B of Table 5, but this time including the deaths recorded in 2008 VS.[22] Results are reported in Panel B of Table 9. It appears that the age and race coefficients are similar in Panels A and B of Table 9, suggesting that the 1990 NLS have similar quality of reporting of deaths as the 2008 VS. All in all, these results suggest that the 2008 VS death reports are quite close to those in the 1990 NLS, and they are much

[20] The results of analyses using data up through 1983 are given in the appendix (see Appendix Tables B). The basic pattern is similar to analyses using data up through 1990.

[21] Further adjustments have been made for cases reporting out of range age at deaths (died before 1966 or died after 1990).

[22] After checking the death reporting between all the NLS surveys and the 1990 VS, a group of 382 men are found to be likely deaths without death certificates (see Section 3.4). Preliminary examination shows that the 2008 VS also reports this group of 382 men as dead (with age at death younger than the comparable group who with deaths with death certificates).

better than the death records in 1990 VS.[23]

Lastly, in Table 10, I try another exercise. With the idea from analyses in Table 9, here I check the death reporting between all the approaches using the NLS survey.[24] Results parallel those reported above.

In sum, this analysis provides strong evidence about the biases in regression coefficients that arise due to the non-classical measurement error in deaths reported. Age and race coefficients in survival analysis are clearly and seriously biased using data such as the 1990 VS match in the NLS-OM.

5 Conclusion

A large and growing literature seeks to understand the role of life-course events for mortality, and often this work stretches back to early childhood. This research often relies on longitudinal data. Such data is subject to a variety of problems, one of which is discussed here: often researchers will have incomplete records of deaths for a sample.

The initial contribution of this paper is to study the nature of the biases that are introduced when researchers face measurement error in mortality. Using a very simple model, I am able to make some useful observations. The main methodological findings include:

First, if the source of identification in the model is cross-sectional, reasonably consistent inference of key parameters in the regression might be possible as long as the mismeasurement of mortality is the same for all key demographic groups (e.g., if unrecorded deaths are not related to age or race).

Second, in data in which identification comes in part from longitudinal variation, the "age coefficient" in a survival regression is likely to be biased downward even when the age-specific rate of measurement error is the same across ages.

Third, if deaths are under-recorded at higher rates for one racial group than another, it is likely to under-estimate the role of race on mortality outcomes for the under-recorded group.

With these lessons in mind, I also provide an empirical application of mismeasurement in deaths. My example comes from the NLS Older Men data (which include death certificate data). I find that in the 1990 data, which are widely used for mortality analysis, there are a fairly large number of men who likely died for whom there was no matched death certificate data. These "omitted deaths" in the data are clearly non-random. In general, blacks are much more likely to be in this group than whites. This is especially true of black men who die at young ages. There are reasons to believe that the NLS responses (e.g., from information provided by the family of the deceased) contain less measurement error

[23] I have repeated the analysis in Tables 7 and 8 using the 1990 NLS and 2008 VS. Results show that the 1990 NLS responses have similar reporting of deaths as the 2008 VS as they produce similar estimates for key parameters. See Appendix Tables C.

[24] Further adjustments are made for cases with out of range reporting of age at deaths (died before the first interview or after the last interview).

than death certificates. Inclusion of these deaths in the analysis proves to move estimated parameters by a fair amount.

Importantly, I provide additional evidence using the newly matched data from vital records collected in 2008. The 2008 Vital Statistics data are seen to have better quality of death reporting than the 1990 death certificate data. The results confirm that the 1990 Census matched death records indeed missed a substantial number of deaths in systematic ways. This mismeasurement of mortality has a significant impact on the inferences about the black-white mortality disparity. It appears that the 2008 Vital Statistics data have similar quality of reporting for deaths as the NLS responses. Both data sets probably give reports that are close to actual outcomes.

One very important point in this work is that researchers cannot hope to get rid of biases introduced by mismeasurement by adopting the seemingly sensible rule of "excluding inconsistent records." When they restrict attention only to data that have completed records, they often will be excluding cases that are *not* missing at random, and biases can thereby be introduced.

As for the empirical application itself—black-white differences in mortality among men born in the early part of the twentieth century—it is found that black men have substantially higher age-specific mortality than white men, even when controlling for childhood factors, and that gap is larger than has been estimated in previous literature. The "preferred" estimates are almost certainly more accurate than estimates derived with regressions that handle the data improperly (i.e., ignoring the missing deaths or simply excluding cases with inconsistent or incomplete records). It is clear from this work that measurement error in mortality is a serious problem in the NLS-OM data, and is likely a serious problem in many other comparable data sets.

The central lesson concerns the practice of matching death records obtained from administrative data to other data sources. While such an approach can give researchers invaluable data for the purpose of studying factors that contribute to mortality, there is the danger of introducing a peculiar form of measurement error that can significantly impact statistical inference. In future work I intend to extend the scope of this paper, using Bayesian approaches to better understand how to analyze data when this type of measurement error is an issue.

Table 1: Childhood Characteristics of NLS Older Men

Variable	Percentage
Household Head's Education#	
6 years or less	24.99
7-8 years	20.31
9-12 years	10.77
13 or more years	6.41
Missing	37.52
Household Head's Occupation#	
Professional or military	4.05
Managerial	11.89
Clerical	1.92
Sales	3.06
Crafts	13.47
Operative	12.4
Private household or service worker	5.36
Farmer	32.22
Farm laborer	1.46
Laborer	6.30
Missing	7.88
Foreign Born	6.17
Parent's Nativity	
One parent was foreign born	6.57
Two parents were foreign born	20.95
Neither parent was foreign born	70.54
NA	1.94
Living Arrangement#	
Father and mother	75.17
Father and stepmother	1.73
Mother and stepfather	2.11
Father only	3.13
Mother only	8.68
Other	8.69
NA	0.50
Mother's Work Status#	
Did not work	59.60
Worked	10.88
Missing	29.52
Childhood Urban/Rural Residence	
City with 100,000 or more people	19.79
City with 25,000-100,000 or more people	10.76
Suburb of a large city	2.38
Town with fewer than 25,000 people	27.29
Rural nonfarm area	3.70
Rural farm area	35.54
NA	0.53

Notes: Weighted percentages are calculated using sampling weights provided by 1966 NLS-OM data. #variables provide information when the respondent at age 15.

Table 2: Adulthood Characteristics of NLS Older Men

Variable	Percentage or Mean
Demographic Characteristics	
Age (mean)	51.55
Black	8.69
Birth Cohort	
1906-1910	27.72
1911-1915	33.34
1916-1921	38.94
Education	
8 years or less	35.42
9-12 years	45.97
13 or more years	18.60
Marital Status	
Married	89.28
Never married	4.57
Divorced	4.23
Widowed	1.92
Urban/Rural Residence	
Urban	49.73
Outside urban	16.52
Rural	33.75
Net Asset (mean)	21717.17
Total Family Income (mean)	7462.867
Body Mass Index	
Under 20	3.29
20-23	13.63
23.1-25	18.01
25.1-27.5	25.45
27.6-52.1	18.02
Missing	21.60
Mean Weekly Alcohol Consumption	
1-2 drinks	19.51
3-4 drinks	5.85
5 or more drinks	5.37
Missing	69.27
Smoking Behavior 1	
Currently smoking	13.09
Currently not smoking	86.91
Smoking Behavior 2	
Never smoked	33.87
Ever smoked	66.13

Notes: All statistics are weighted using sampling weights provided by 1966 NLS-OM data. Net asset and total family income are in dollars; all negative values of net asset and total family income are adjusted to zero.

Table 3: Survival Regression Results for Data up through 1983

A. Deaths with Death Certificate Records

	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.068***	0.069***	0.069***
	(0.018)	(0.018)	(0.018)	(0.018)
Black	0.166***	0.155**	0.159**	0.187***
	(0.063)	(0.065)	(0.065)	(0.064)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

B. Including Deaths from NLS Records

	Model 1	Model 2	Model 3	Model 4
Age	0.058***	0.056***	0.058***	0.057***
	(0.016)	(0.016)	(0.016)	(0.016)
Black	0.351***	0.331***	0.339***	0.376***
	(0.054)	(0.055)	(0.055)	(0.055)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

C. Discarding Inconsistent Records

	Model 1	Model 2	Model 3	Model 4
Age	0.058***	0.058***	0.060***	0.059***
	(0.020)	(0.020)	(0.020)	(0.020)
Black	0.279***	0.258***	0.265***	0.299***
	(0.067)	(0.068)	(0.069)	(0.068)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4326	4326	4317	4321

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Table 4: Comparisons Between Characteristics of Individuals with Deaths *without* Death Certificates (NLS 382 Men) and Individuals with Deaths *with* Death Certificates (NLS 1116 Men)

	Percentage or Mean	
Variable	382 Men	1116 Men
Demographic Characteristics		
Age (mean)	52.44	52.82
Black	16.22	10.54
Birth Cohort		
1906-1910	35.46	39.07
1911-1915	37.74	34.65
1916-1921	26.80	26.28
Age at Death (mean)	62.02	62.95
Cohort (1906-1910)	65.74	67.23
Cohort (1911-1915)	62.19	62.11
Cohort (1916-1921)	56.50	57.79
Black	61.55	62.88
White	62.11	62.96
Foreign born	62.40	62.58
Not foreign born	61.96	62.99
Education		
8 years or less	42.41	44.39
9-12 years	41.25	43.12
13 or more years	16.34	12.50
Marital Status		
Married	78.25	88.10
Never married	8.89	4.06
Divorced	7.80	5.25
Widowed	5.06	2.59
Urban/Rural Residence		
Urban	55.18	47.43
Outside urban	13.58	17.80
Rural	31.25	34.77
Net Asset (mean)	15320.48	16517.5
Excluding missing values	18914.47	20289.49
Total Family Income (mean)	6233.992	6325.498
Excluding missing values	7653.39	7838.9

Notes: All statistics are weighted using sampling weights provided by 1966 NLS-OM data. Net asset and total family income are in dollars; all negative values of net asset and total family income are adjusted to zero. "Excluding missing values" considers all cases (including all positive and negative values) for net asset and total family income except cases with missing data.

Table 5: Survival Regression Results for Data up through 1990

A. Deaths with Death Certificate Records

	Model 1	Model 2	Model 3	Model 4
Age	0.072***	0.072***	0.073***	0.073***
	(0.014)	(0.014)	(0.014)	(0.014)
Black	0.120**	0.107**	0.114**	0.136***
	(0.049)	(0.050)	(0.051)	(0.050)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

B. Including Deaths from NLS Records

	Model 1	Model 2	Model 3	Model 4
Age	0.065***	0.063***	0.066***	0.064***
	(0.013)	(0.013)	(0.013)	(0.013)
Black	0.281***	0.262***	0.271***	0.302***
	(0.044)	(0.046)	(0.046)	(0.045)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

C. Discarding Inconsistent Records

	Model 1	Model 2	Model 3	Model 4
Age	0.072***	0.071***	0.073***	0.072***
	(0.015)	(0.015)	(0.015)	(0.015)
Black	0.228***	0.208***	0.214***	0.245***
	(0.051)	(0.053)	(0.053)	(0.052)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4326	4326	4317	4321

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Table 6: Death Records

A. 1990 Vital Statistics Compared with 2008 Vital Statistics

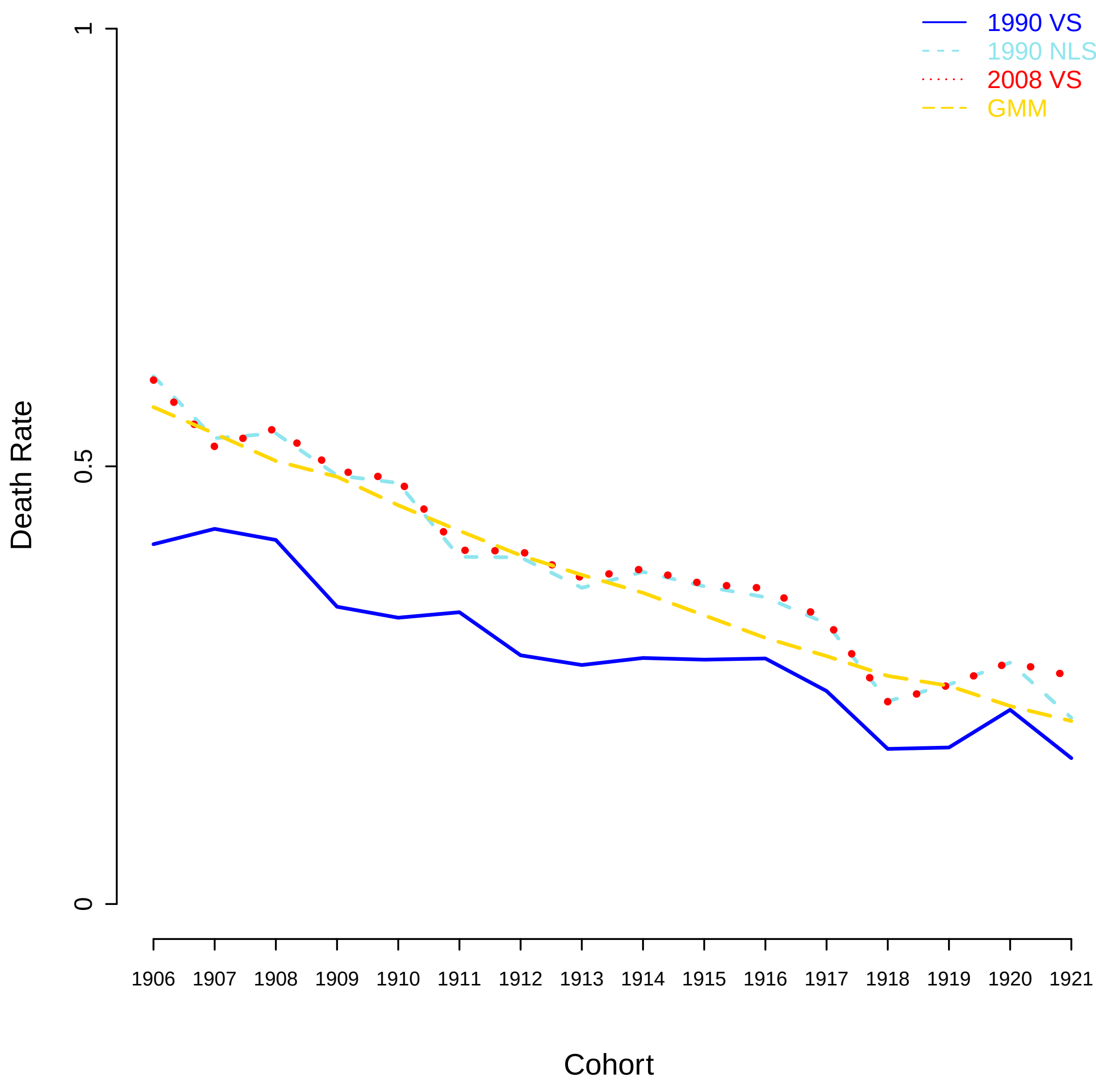
	1990 VS	2008 VS	N	Age in 1966	% Black	1990 VS Death Age	2008 VS Death Age
False Negative in 1990	−	+	609	52.39	14	-	66.05
False Positive in 1990	+	−	42	52.62	23	58.97	-
Age of Death Mismatched			70	51.25	13	66.71	70.85
Death Likely after 1990		+	2007	50.80	7	-	82.89
Correct Match (Alive)	−	−	321	48.16	8	-	-
Correct Match (Dead)	+	+	1971	52.68	9	67.88	67.88
Total			5020	51.55	9	67.71	74.53

B. 1990 NLS Death Reports Compared with 2008 Vital Statistics

	1990 NLS	2008 VS	N	Age in 1966	% Black	1990 NLS Death Age	2008 VS Death Age
False Negative in 1990	−	+	48	51.63	13	-	67.98
False Positive in 1990	+	−	42	52.62	23	59.55	-
Age of Death Mismatch			98	52.18	19	66.45	71.76
Death Likely after 1990		+	1991	50.79	7	-	82.91
Correct Match (Alive)	−	−	321	48.16	8	-	-
Correct Match (Dead)	+	+	2520	52.61	10	67.49	67.49
Total			5020	51.55	9	67.36	74.53

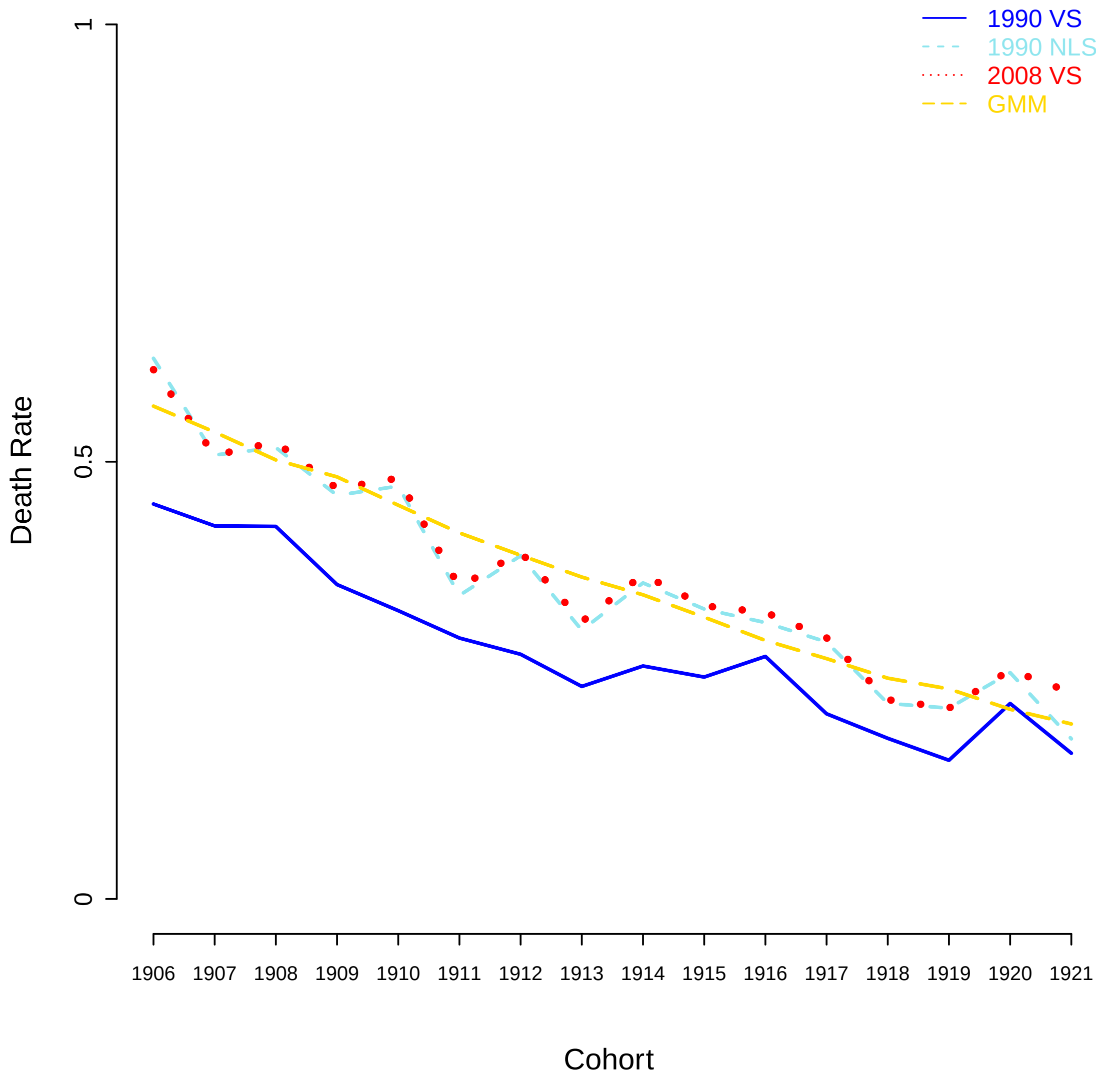
Note: All statistics are weighted using sampling weights provided by 1966 NLS-OM data. − indicates that no death is reported; + indicates a reported death.

Figure 1: Ten-Year Death Rates, 1980 to 1990, by Cohort (1906-1921), NLS-Older Men



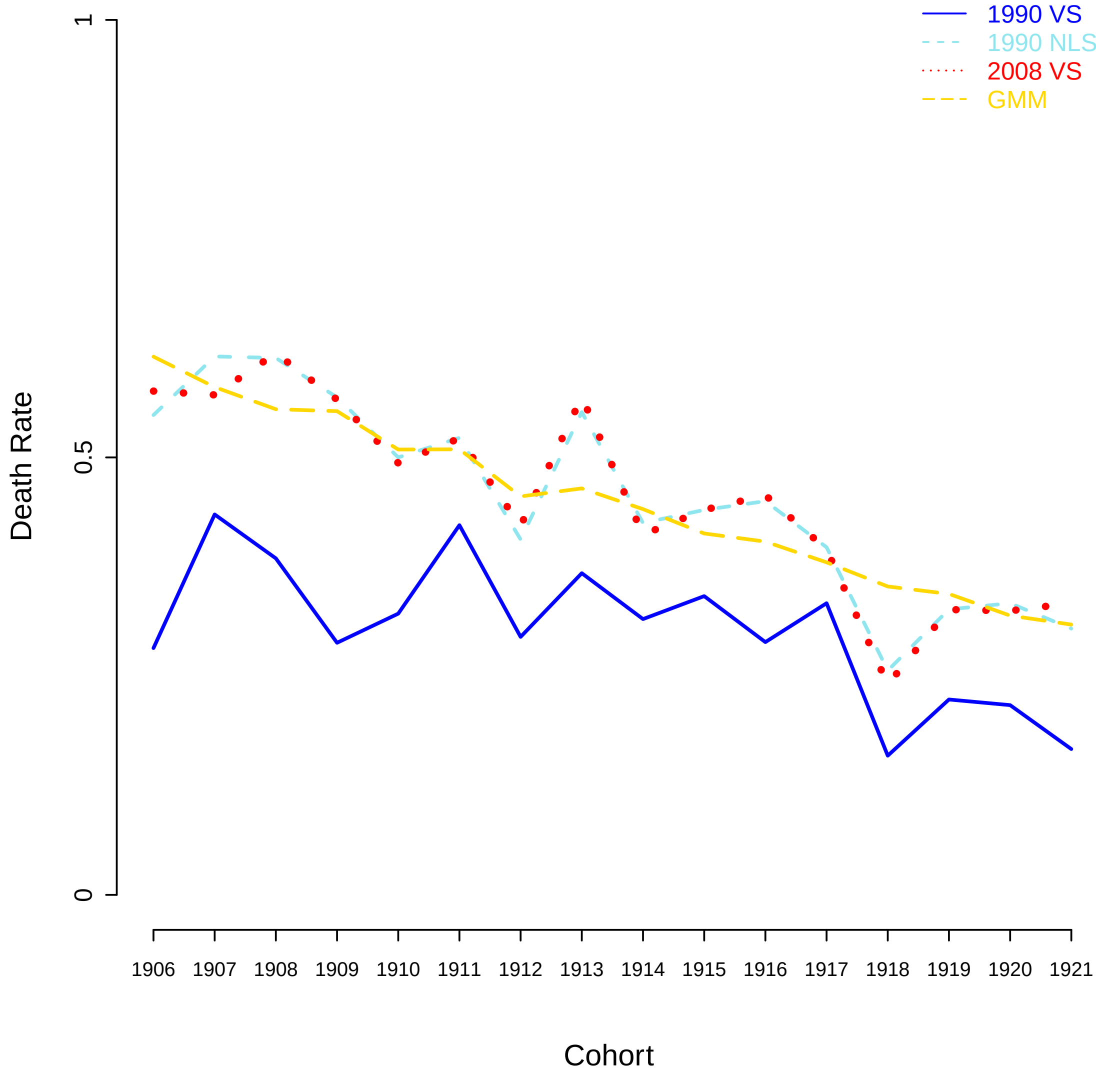
Source: Author's calculations, data from 1990 Vital Statistics, 1990 NLS, 2008 Vital Statistics, and GMM estimates using data from the 1980 and 1990 Census and Vital Statistics.

Figure 2: Ten-Year Death Rates, 1980 to 1990, by Cohort (1906-1921), NLS-Older Men, White



Source: Author's calculations, data from 1990 Vital Statistics, 1990 NLS, 2008 Vital Statistics, and GMM estimates using data from the 1980 and 1990 Census and Vital Statistics.

Figure 3: Ten-Year Death Rates, 1980 to 1990, by Cohort (1906-1921), NLS-Older Men, Black



Source: Author's calculations, data from 1990 Vital Statistics, 1990 NLS, 2008 Vital Statistics, and GMM estimates using data from the 1980 and 1990 Census and Vital Statistics.

Table 7: Survival Regression Results for Data up through 1990, Deaths with 1990 VS and 2008 VS

A. Deaths with 1990 Death Certificate Records				
	Model 1	Model 2	Model 3	Model 4
Age	0.072***	0.072***	0.073***	0.073***
	(0.014)	(0.014)	(0.014)	(0.014)
Black	0.120**	0.107**	0.114**	0.136***
	(0.049)	(0.050)	(0.051)	(0.050)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

B. Deaths from 2008 Vital Statistics				
	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.068***	0.070***	0.069***
	(0.012)	(0.012)	(0.012)	(0.012)
Black	0.285***	0.264***	0.278***	0.313***
	(0.043)	(0.044)	(0.044)	(0.044)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Table 8: Survival Regression Results for Data up through 1990, Correcting 1990 VS Data Using 2008 VS

A. Excluding Inconsistent Records

	Model 1	Model 2	Model 3	Model 4
Age	0.074***	0.073***	0.074***	0.074***
	(0.015)	(0.015)	(0.015)	(0.015)
Black	0.062	0.048	0.060	0.080
	(0.051)	(0.052)	(0.052)	(0.052)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	2271	2271	2265	2267

B. Correcting for False Negative Cases Using 2008 VS

	Model 1	Model 2	Model 3	Model 4
Age	0.071***	0.070***	0.072***	0.070***
	(0.012)	(0.012)	(0.012)	(0.012)
Black	0.315***	0.295***	0.304***	0.344***
	(0.042)	(0.043)	(0.044)	(0.043)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

C. Correcting for Death Age Mismatched Cases Using 2008 VS

	Model 1	Model 2	Model 3	Model 4
Age	0.074***	0.073***	0.074***	0.074***
	(0.014)	(0.014)	(0.014)	(0.014)
Black	0.113**	0.101**	0.108**	0.127**
	(0.049)	(0.051)	(0.051)	(0.050)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

D. Correcting for False Positive Cases Using 2008 VS

	Model 1	Model 2	Model 3	Model 4
Age	0.070***	0.070***	0.071***	0.070***
	(0.014)	(0.014)	(0.014)	(0.014)
Black	0.086*	0.071	0.083	0.105**
	(0.050)	(0.051)	(0.051)	(0.051)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

E. Correcting for All Mismeasured Cases Using 2008 VS

	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.068***	0.071***	0.069***
	(0.012)	(0.013)	(0.012)	(0.012)
Black	0.282***	0.261***	0.275***	0.311***
	(0.043)	(0.044)	(0.044)	(0.044)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Table 9: Survival Regression Results for Data up through 1990, Checked Data Including Deaths from 1990 NLS and 2008 VS

A. Including Deaths from 1990 NLS Records

	Model 1	Model 2	Model 3	Model 4
Age	0.065***	0.063***	0.066***	0.064***
	(0.013)	(0.013)	(0.013)	(0.013)
Black	0.281***	0.262***	0.271***	0.302***
	(0.044)	(0.046)	(0.046)	(0.045)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

B. Including Deaths from 2008 Vital Statistics

	Model 1	Model 2	Model 3	Model 4
Age	0.065***	0.064***	0.066***	0.065***
	(0.013)	(0.013)	(0.013)	(0.013)
Black	0.283***	0.265***	0.273***	0.305***
	(0.044)	(0.046)	(0.046)	(0.045)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Table 10: Survival Regression Results for Data up through 1990, Data Checked Using NLS Responses

A. Deaths with 1990 Death Certificate Records				
	Model 1	Model 2	Model 3	Model 4
Age	0.070***	0.070***	0.071***	0.070***
	(0.014)	(0.014)	(0.014)	(0.014)
Black	0.119**	0.107**	0.113**	0.135***
	(0.049)	(0.050)	(0.051)	(0.050)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

B. Deaths from 1990 NLS Records				
	Model 1	Model 2	Model 3	Model 4
Age	0.067***	0.066***	0.068***	0.067***
	(0.012)	(0.012)	(0.012)	(0.012)
Black	0.306***	0.286***	0.296***	0.333***
	(0.043)	(0.044)	(0.044)	(0.043)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

C. Deaths from 2008 Vital Statistics				
	Model 1	Model 2	Model 3	Model 4
Age	0.066***	0.065***	0.068***	0.066***
	(0.012)	(0.012)	(0.012)	(0.012)
Black	0.286***	0.265***	0.279***	0.316***
	(0.043)	(0.044)	(0.044)	(0.043)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates. Data have checked the death reporting between all the NLS surveys and each of these death data.

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Appendix Tables A.

Table A.1: Effect of Early-Life Characteristics on Men's Mortality, NLS Older Men

	Sample A (up through 1983)			
	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.068***	0.069***	0.069***
	(0.018)	(0.018)	(0.018)	(0.018)
Black	0.166***	0.155**	0.159**	0.187***
	(0.063)	(0.065)	(0.065)	(0.064)
Cohort (reference: 1906-1910)				
1911-1915	-0.007	-0.008	-0.009	-0.010
	(0.110)	(0.110)	(0.110)	(0.110)
1916-1921	-0.100	-0.101	-0.096	-0.106
	(0.192)	(0.192)	(0.192)	(0.193)
R foreign born	-0.456***	-0.455***	-0.448***	-0.471***
	(0.157)	(0.157)	(0.157)	(0.157)
Education of head of household (reference: ≤6 years)				
Missing		0.039		
		(0.072)		
7-8 years		-0.033		
		(0.093)		
9-12 years		0.080		
		(0.110)		
13- years		-0.114		
		(0.152)		
Family structure (reference: mother and father)				
Father and stepmother			-0.024	
			(0.227)	
Mother and stepfather			0.286	
			(0.180)	
Father only			0.238	
			(0.147)	
Mother only			-0.083	
			(0.103)	
Male relative			0.283**	
			(0.136)	
Other arrangement			-0.008	
			(0.128)	
Living on his own			0.171	
			(0.233)	
Community size (reference: large city 100,000+)				
Smaller city (25,000-100,000)				-0.107
				(0.119)
Suburb of a large city				-0.097
				(0.234)
Town less than 25,000				0.153*
				(0.089)
Rural, non-farm				0.247*
				(0.147)
Rural, farm				-0.039
				(0.085)
Constant	-7.748***	-7.732***	-7.778***	-7.764***
	(1.045)	(1.047)	(1.046)	(1.050)
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%.

Table A.2: Effect of Early-Life Characteristics on Men's Mortality, NLS Older Men

	Sample B (up through 1983)			
	Model 1	Model 2	Model 3	Model 4
Age	0.058***	0.056***	0.058***	0.057***
	(0.016)	(0.016)	(0.016)	(0.016)
Black	0.351***	0.331***	0.339***	0.376***
	(0.054)	(0.055)	(0.055)	(0.055)
Birth cohort (reference: 1906-1910)				
1911-1915	-0.060	-0.065	-0.059	-0.063
	(0.096)	(0.096)	(0.096)	(0.096)
1916-1921	-0.203	-0.209	-0.195	-0.214
	(0.167)	(0.167)	(0.167)	(0.167)
R foreign born	-0.016	-0.014	-0.008	-0.039
	(0.116)	(0.116)	(0.116)	(0.117)
Education of head of household (reference: $\leq$6 years)				
Missing		0.085		
		(0.062)		
7-8 years		-0.042		
		(0.082)		
9-12 years		0.050		
		(0.097)		
13- years		-0.093		
		(0.133)		
Family structure (reference: mother and father)				
Father and stepmother			-0.129	
			(0.207)	
Mother and stepfather			0.247	
			(0.163)	
Father only			0.109	
			(0.135)	
Mother only			0.009	
			(0.086)	
Male relative			0.180	
			(0.122)	
Other arrangement			0.040	
			(0.107)	
Living on his own			0.355*	
			(0.189)	
Community size (reference: large city 100,000+)				
Smaller city (25,000-100,000)				-0.201*
				(0.103)
Suburb of a large city				-0.046
				(0.192)
Suburb of a large city				0.025
				(0.077)
Rural, non-farm				0.147
				(0.128)
Rural, farm				-0.132*
				(0.072)
Constant	-6.879***	-6.823***	-6.931***	-6.795***
	(0.906)	(0.908)	(0.907)	(0.910)
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%.

Table A.3: Effect of Early-Life Characteristics on Men's Mortality, NLS Older Men

	Sample C (up through 1983)			
	Model 1	Model 2	Model 3	Model 4
Age	0.058***	0.058***	0.060***	0.059***
	(0.020)	(0.020)	(0.020)	(0.020)
Black	0.279***	0.258***	0.265***	0.299***
	(0.067)	(0.068)	(0.069)	(0.068)
Birth cohort (reference: 1906-1910)				
1911-1915	-0.114	-0.114	-0.113	-0.112
	(0.118)	(0.118)	(0.118)	(0.118)
1916-1921	-0.357*	-0.356*	-0.344*	-0.357*
	(0.207)	(0.207)	(0.207)	(0.207)
R foreign born	-0.509***	-0.512***	-0.502***	-0.525***
	(0.178)	(0.179)	(0.178)	(0.179)
Education of head of household (reference: ≤6 years)				
Missing		0.027		
		(0.076)		
7-8 years		-0.085		
		(0.099)		
9-12 years		0.046		
		(0.117)		
13- years		-0.201		
		(0.165)		
Family structure (reference: mother and father)				
Father and stepmother			-0.097	
			(0.253)	
Mother and stepfather			0.307	
			(0.190)	
Father only			0.241	
			(0.156)	
Mother only			-0.096	
			(0.111)	
Male relative			0.303**	
			(0.142)	
Other arrangement			0.055	
			(0.133)	
Living on his own			0.355	
			(0.239)	
Community size (reference: large city 100,000+)				
Smaller city (25,000-100,000)				-0.135
				(0.130)
Suburb of a large city				0.065
				(0.236)
Town less than 25,000				0.154
				(0.097)
Rural, non-farm				0.294*
				(0.155)
Rural, farm				-0.026
				(0.092)
Constant	-7.079***	-7.035***	-7.180***	-7.136***
	(1.122)	(1.125)	(1.123)	(1.125)
N	4326	4326	4317	4321

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%.

Table A.4: Effect of Early-Life Characteristics on Men's Mortality, NLS Older Men

	Sample A (up through 1990)			
	Model 1	Model 2	Model 3	Model 4
Age	0.072***	0.072***	0.073***	0.073***
	(0.014)	(0.014)	(0.014)	(0.014)
Black	0.120**	0.107**	0.114**	0.136***
	(0.049)	(0.050)	(0.051)	(0.050)
Cohort (reference: 1906-1910)				
1911-1915	0.008	0.009	0.015	0.008
	(0.085)	(0.085)	(0.086)	(0.086)
1916-1921	0.007	0.008	0.017	0.004
	(0.148)	(0.148)	(0.148)	(0.148)
R foreign born	-0.499***	-0.500***	-0.506***	-0.515***
	(0.121)	(0.121)	(0.122)	(0.121)
Education of head of household (reference: ≤6 years)				
Missing		0.006		
		(0.055)		
7-8 years		-0.054		
		(0.071)		
9-12 years		0.009		
		(0.086)		
13- years		-0.109		
		(0.114)		
Family structure (reference: mother and father)				
Father and stepmother			-0.018	
			(0.174)	
Mother and stepfather			0.378***	
			(0.135)	
Father only			0.166	
			(0.118)	
Mother only			0.013	
			(0.076)	
Male relative			0.139	
			(0.113)	
Other arrangement			0.029	
			(0.097)	
Living on his own			-0.056	
			(0.202)	
Community size (reference: large city 100,000+)				
Smaller city (25,000-100,000)				0.059
				(0.089)
Suburb of a large city				0.169
				(0.164)
Town less than 25,000				0.187***
				(0.070)
Rural, non-farm				0.198*
				(0.119)
Rural, farm				0.023
				(0.066)
Constant	-7.699***	-7.670***	-7.771***	-7.787***
	(0.804)	(0.805)	(0.805)	(0.808)
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%.

Table A.5: Effect of Early-Life Characteristics on Men's Mortality, NLS Older Men

	Sample B (up through 1990)			
	Model 1	Model 2	Model 3	Model 4
Age	0.065***	0.063***	0.066***	0.064***
	(0.013)	(0.013)	(0.013)	(0.013)
Black	0.281***	0.262***	0.271***	0.302***
	(0.044)	(0.046)	(0.046)	(0.045)
Birth cohort (reference: 1906-1910)				
1911-1915	-0.049	-0.051	-0.041	-0.051
	(0.078)	(0.078)	(0.078)	(0.078)
1916-1921	-0.111	-0.114	-0.098	-0.122
	(0.135)	(0.135)	(0.135)	(0.135)
R foreign born	-0.166*	-0.166*	-0.167*	-0.188*
	(0.099)	(0.099)	(0.100)	(0.100)
Education of head of household (reference: ≤6 years)				
Missing		0.051		
		(0.051)		
7-8 years		-0.057		
		(0.066)		
9-12 years		0.000		
		(0.079)		
13- years		-0.090		
		(0.105)		
Family structure (reference: mother and father)				
Father and stepmother			-0.101	
			(0.164)	
Mother and stepfather			0.360***	
			(0.128)	
Father only			0.083	
			(0.111)	
Mother only			0.059	
			(0.069)	
Male relative			0.090	
			(0.105)	
Other arrangement			0.056	
			(0.087)	
Living on his own			0.161	
			(0.171)	
Community size (reference: large city 100,000+)				
Smaller city (25,000-100,000)				-0.043
				(0.081)
Suburb of a large city				0.150
				(0.147)
Town less than 25,000				0.085
				(0.064)
Rural, non-farm				0.137
				(0.108)
Rural, farm				-0.062
				(0.060)
Constant	-7.064***	-7.008***	-7.158***	-7.047***
	(0.735)	(0.737)	(0.736)	(0.739)
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%.

Table A.6: Effect of Early-Life Characteristics on Men's Mortality, NLS Older Men

	Sample C (up through 1990)			
	Model 1	Model 2	Model 3	Model 4
Age	0.072***	0.071***	0.073***	0.072***
	(0.015)	(0.015)	(0.015)	(0.015)
Black	0.228***	0.208***	0.214***	0.245***
	(0.051)	(0.053)	(0.053)	(0.052)
Birth cohort (reference: 1906-1910)				
1911-1915	-0.043	-0.042	-0.034	-0.042
	(0.090)	(0.090)	(0.090)	(0.090)
1916-1921	-0.121	-0.120	-0.105	-0.124
	(0.157)	(0.157)	(0.157)	(0.157)
R foreign born	-0.460***	-0.464***	-0.470***	-0.482***
	(0.130)	(0.130)	(0.131)	(0.131)
Education of head of household (reference: ≤6 years)				
Missing		0.014		
		(0.058)		
7-8 years		-0.079		
		(0.074)		
9-12 years		-0.004		
		(0.090)		
13- years		-0.156		
		(0.121)		
Family structure (reference: mother and father)				
Father and stepmother			-0.101	
			(0.191)	
Mother and stepfather			0.412***	
			(0.140)	
Father only			0.184	
			(0.122)	
Mother only			0.027	
			(0.080)	
Male relative			0.149	
			(0.117)	
Other arrangement			0.076	
			(0.101)	
Living on his own			0.087	
			(0.211)	
Community size (reference: large city 100,000+)				
Smaller city (25,000-100,000)				0.021
				(0.095)
Suburb of a large city				0.256
				(0.167)
Town less than 25,000				0.157**
				(0.074)
Rural, non-farm				0.203
				(0.124)
Rural, farm				0.001
				(0.070)
Constant	-7.573***	-7.525***	-7.702***	-7.648***
	(0.853)	(0.854)	(0.853)	(0.856)
N	4326	4326	4317	4321

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%.

Appendix Tables B.

Table B.1: Survival Regression Results for Data up through 1983, Deaths with 1990 VS and 2008 VS

A. Deaths with 1990 Death Certificate Records

	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.068***	0.069***	0.069***
	(0.018)	(0.018)	(0.018)	(0.018)
Black	0.166***	0.155**	0.159**	0.187***
	(0.063)	(0.065)	(0.065)	(0.064)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

B. Deaths from 2008 Vital Statistics

	Model 1	Model 2	Model 3	Model 4
Age	0.061***	0.059***	0.061***	0.061***
	(0.016)	(0.016)	(0.016)	(0.016)
Black	0.315***	0.299***	0.314***	0.343***
	(0.055)	(0.056)	(0.056)	(0.056)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Table B.2: Survival Regression Results for Data up through 1983, Correcting 1990 VS Data Using 2008 VS

A. Excluding Inconsistent Records

	Model 1	Model 2	Model 3	Model 4
Age	0.065***	0.064***	0.064***	0.064***
	(0.019)	(0.019)	(0.019)	(0.019)
Black	0.090	0.077	0.090	0.108
	(0.066)	(0.067)	(0.067)	(0.067)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	2271	2271	2265	2267

B. Correcting for False Negative Cases Using 2008 VS

	Model 1	Model 2	Model 3	Model 4
Age	0.064***	0.062***	0.064***	0.063***
	(0.016)	(0.016)	(0.016)	(0.016)
Black	0.354***	0.339***	0.346***	0.382***
	(0.054)	(0.055)	(0.055)	(0.055)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

C. Correcting for Death Age Mismatched Cases Using 2008 VS

	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.069***	0.069***	0.069***
	(0.018)	(0.018)	(0.018)	(0.018)
Black	0.157**	0.147**	0.154**	0.174***
	(0.063)	(0.065)	(0.065)	(0.065)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

D. Correcting for False Positive Cases Using 2008 VS

	Model 1	Model 2	Model 3	Model 4
Age	0.066***	0.066***	0.066***	0.066***
	(0.019)	(0.019)	(0.019)	(0.019)
Black	0.120*	0.106	0.118*	0.145**
	(0.064)	(0.066)	(0.066)	(0.066)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

E. Correcting for All Mismeasured Cases Using 2008 VS

	Model 1	Model 2	Model 3	Model 4
Age	0.061***	0.059***	0.061***	0.061***
	(0.016)	(0.016)	(0.016)	(0.016)
Black	0.315***	0.299***	0.314***	0.343***
	(0.055)	(0.056)	(0.056)	(0.056)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Table B.3: Survival Regression Results for Data up through 1983, Checked Data Including Deaths from 1990 NLS and 2008 VS

A. Including Deaths from 1990 NLS Records

	Model 1	Model 2	Model 3	Model 4
Age	0.058***	0.056***	0.058***	0.057***
	(0.016)	(0.016)	(0.016)	(0.016)
Black	0.351***	0.331***	0.339***	0.376***
	(0.054)	(0.055)	(0.055)	(0.055)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

B. Including Deaths from 2008 Vital Statistics

	Model 1	Model 2	Model 3	Model 4
Age	0.058***	0.057***	0.059***	0.058***
	(0.016)	(0.016)	(0.016)	(0.016)
Black	0.353***	0.334***	0.341***	0.378***
	(0.054)	(0.055)	(0.055)	(0.055)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Table B.4: Survival Regression Results for Data up through 1983, Data Checked Using NLS Responses

A. Deaths with 1990 Death Certificate Records				
	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.068***	0.069***	0.069***
	(0.018)	(0.018)	(0.018)	(0.018)
Black	0.166***	0.155**	0.159**	0.187***
	(0.063)	(0.065)	(0.065)	(0.064)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964
B. Deaths from 1990 NLS Records				
	Model 1	Model 2	Model 3	Model 4
Age	0.064***	0.062***	0.064***	0.063***
	(0.016)	(0.016)	(0.016)	(0.016)
Black	0.348***	0.331***	0.340***	0.376***
	(0.054)	(0.055)	(0.055)	(0.055)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964
C. Deaths from 2008 Vital Statistics				
	Model 1	Model 2	Model 3	Model 4
Age	0.061***	0.059***	0.061***	0.061***
	(0.016)	(0.016)	(0.016)	(0.016)
Black	0.315***	0.299***	0.314***	0.343***
	(0.055)	(0.056)	(0.056)	(0.056)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates. Data have checked the death reporting between all the NLS surveys and each of these death data.

Appendix Tables C.

Table C.1: Survival Regression Results for Data up through 1990, Deaths with 1990 NLS and 2008 VS

A. Deaths from 1990 NLS Records

	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.068***	0.070***	0.068***
	(0.012)	(0.012)	(0.012)	(0.012)
Black	0.307***	0.286***	0.297***	0.334***
	(0.043)	(0.044)	(0.044)	(0.043)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

B. Deaths from 2008 Vital Statistics

	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.068***	0.070***	0.069***
	(0.012)	(0.012)	(0.012)	(0.012)
Black	0.285***	0.264***	0.278***	0.313***
	(0.043)	(0.044)	(0.044)	(0.044)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Table C.2: Survival Regression Results for Data up through 1990, Correcting 1990 NLS Data Using 2008 VS

A. Excluding inconsistent Records				
	Model 1	Model 2	Model 3	Model 4
Age	0.065***	0.063***	0.065***	0.064***
	(0.013)	(0.013)	(0.013)	(0.013)
Black	0.092**	0.079*	0.090**	0.106**
	(0.044)	(0.045)	(0.045)	(0.045)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	2813	2813	2806	2809
B. Correcting for False Negative Cases Using 2008 VS				
	Model 1	Model 2	Model 3	Model 4
Age	0.071***	0.069***	0.072***	0.070***
	(0.012)	(0.012)	(0.012)	(0.012)
Black	0.320***	0.299***	0.310***	0.348***
	(0.042)	(0.043)	(0.044)	(0.043)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964
C. Correcting for Death Age Mismatched Cases Using 2008 VS				
	Model 1	Model 2	Model 3	Model 4
Age	0.070***	0.069***	0.071***	0.069***
	(0.012)	(0.012)	(0.012)	(0.012)
Black	0.297***	0.277***	0.287***	0.322***
	(0.043)	(0.044)	(0.044)	(0.044)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964
D. Correcting for False Positive Cases Using 2008 VS				
	Model 1	Model 2	Model 3	Model 4
Age	0.067***	0.065***	0.068***	0.066***
	(0.012)	(0.013)	(0.013)	(0.013)
Black	0.279***	0.257***	0.272***	0.309***
	(0.043)	(0.044)	(0.044)	(0.044)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964
E. Correcting for All Mismeasured Cases Using 2008 VS				
	Model 1	Model 2	Model 3	Model 4
Age	0.069***	0.068***	0.071***	0.069***
	(0.012)	(0.013)	(0.012)	(0.012)
Black	0.282***	0.261***	0.275***	0.311***
	(0.043)	(0.044)	(0.044)	(0.044)
Birth cohort	×	×	×	×
R foreign born	×	×	×	×
Education of head of household		×		
Family structure			×	
Community size				×
N	4972	4972	4962	4964

Notes: Standard errors in parentheses. *significant at 10 %; **significant at 5%; ***significant at 1%. × corresponds to unreported/statistically insignificant estimates.

Appendix D. Procedure for GMM Estimation

In Figures 1, 2, and 3, I report GMM estimates of ten-year mortality, 1980-1990, by race for cohorts born in years 1906 through 1921. That is, I estimate $d_i^{1980-1990} = \frac{D_i^{1980-1990}}{N_i^{1980}}$, where i indexes the demographic group in question (i.e., the birth cohort by race). This requires that I have estimates of both $D_i^{1980-1990}$ and N_i^{1980}.

As noted in the text, I assume the 1980-1990 Vital Statistics data give me an accurate count of $D_i^{1980-1990}$. So all that remains is to get the best possible estimate of N_i^{1980}. In principle, one could use the 1980 Census data for this purpose, but we can do better yet by combining the 1980 Census samples with the 1990 Census samples.

Let D_i be the death count from vital records of the number of group i individuals of interest who have died between 1980 and 1990 (which are donated date 0 and date 1 in what follows). Then let N_i^0 be the number of group i individuals alive at date 0, and N_i^1 be the comparable number at date 1. These two numbers are unknown, but they can be estimated using Census and Vital Statistics data. In particular, suppose there is a Census at date 0 that samples at a rate of 1 in ω^0, resulting in a sample of S_i^0 group i individuals. Similarly at date 1 a Census provides a sample of S_i^1 group i individuals with sampling rate 1 in ω^1. Then the calculation can proceed with the following relationships:[25]

$$\begin{aligned} \mathrm{E}\left\{\omega^0 S_i^0 - N_i^0\right\} &= 0, \\ \mathrm{E}\{\omega^1 S_i^1 + D_i - N_i^0\} &= 0. \end{aligned} \tag{19}$$

The expectations in (19) are the "moment restrictions." The idea is to select a value for N_i^0, i.e., the base for calculating mortality, by fitting these restrictions well.

A simple way to proceed is to minimize

$$\left[\begin{array}{cc} N_i^0 - \omega^0 S_i^0 & N_i^0 - \omega^1 S_i^1 - D_i \end{array}\right] \left[\begin{array}{cc} 1 & 0 \\ 0 & 1 \end{array}\right] \left[\begin{array}{c} N_i^0 - \omega^0 S_i^0 \\ N_i^0 - \omega^1 S_i^1 - D_i \end{array}\right], \tag{20}$$

which leads to a minimum distance estimator,

$$\hat{N_i^0} = \frac{1}{2}\left(\omega^0 S_i^0\right) + \frac{1}{2}\left(\omega^1 S_i^1 + D_i\right). \tag{21}$$

This in turn can be used as a first step to form a GMM estimator. As shown in Black, *et al.* (2012), GMM undertakes a similar minimization exercise, such as the one given in (20), but in which the matrix in the interior of (20) replaces the identity matrix with W^{-1}, the inverse of the covariance matrix from the vector of "moment restrictions," which in this case is

$$\begin{aligned} W &= \mathrm{E}\left\{\left[\begin{array}{c} N_i^0 - \omega^0 S_i^0 \\ N_i^0 - \omega^1 S_i^1 - D_i \end{array}\right]\left[\begin{array}{cc} N_i^0 - \omega^0 S_i^0 & N_i^0 - \omega^1 S_i^1 - D_i \end{array}\right]\right\} \\ &= \left[\begin{array}{cc} \left(\omega^0\right)^2 S^0 p_i^0(1-p_i^0) & 0 \\ 0 & \left(\omega^1\right)^2 S^1 p_i^1(1-p_i^1) \end{array}\right], \end{aligned} \tag{22}$$

[25]Notation is slightly more complicated if weights differ across individuals, as noted in Black, *et al.* (2012).

where p_i^0 and p_i^1 are, respectively, the probability at date 0 that an observation from the complete sample S^0 is a member of group i, and the analogous probability at date 1.[26] With a bit of algebra, the resulting estimator, based on the GMM approach, is

$$\begin{aligned}\hat{\hat{N}}_i^0 = &\left[\frac{((\omega^0)^2 S^0 \hat{p}_i^0(1-\hat{p}_i^0))^{-1}}{((\omega^0)^2 S^0 \hat{p}_i^0(1-\hat{p}_i^0))^{-1} + ((\omega^1)^2 S^1 \hat{p}_i^1(1-\hat{p}_i^1))^{-1}}\right]\omega^0 S_i^0 \\ &+ \left[\frac{((\omega^1)^2 S^1 \hat{p}_i^1(1-\hat{p}_i^1))^{-1}}{((\omega^0)^2 S^0 \hat{p}_i^0(1-\hat{p}_i^0))^{-1} + ((\omega^1)^2 S^1 \hat{p}_i^1(1-\hat{p}_i^1))^{-1}}\right]\left(\omega^1 S_i^1 + D_i\right), \qquad (23)\end{aligned}$$

where estimates from the first stage, $\hat{p}_i^0$ and $\hat{p}_i^1$, replace p_i^0 and p_i^1. As in (21), the estimator consists of a weighted sum of two consistent estimates of N_i^0, but in the GMM case those weights are selected so as to minimize the asymptotic variance of the estimator.

Finally, having found the GMM estimate of N_i^0, the estimate of the mortality rate for group i from date 0 to date 1 is

$$d_i = \frac{D_i}{\hat{\hat{N}}_i^0}.$$

In my case, though, I am interested in using the GMM estimate of N_i^0 for the purpose of using it as a base to calculate the ten-year mortality rates, 1980-1990:

$$d_i^{1980-1990} = \frac{D_i^{1980-1990}}{\hat{N}_i^{1980,GMM}},$$

where the denominator is the GMM estimate.

[26]See Black, *et al.* (2012) for a more detailed description.