Testing for changes in the socioeconomic status-mortality gradient when the distribution of education changes too

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December 2015

Abstract

We develop a flexible test for changes in the SES-mortality gradient that accounts for changes in the distribution of education, the most commonly used marker of SES. We implement the test for the period between 1984 and 2006 in the United States using microdata from the Census and other surveys linked to death records. Using our flexible test, we find that the evidence for a change in the SES-mortality gradient is not as strong as previous research has suggested. Our results indicate that the gradient increased for females during this time period, but we cannot rule out that the gradient among males has not changed. Informally, the results suggest that the changes for females are mainly driven by the bottom of the education distribution.

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1 Introduction

Persistent differences in health and longevity across socioeconoimc status (SES) are well-established, and a growing literature claims that these differences have increased over recent decades.[1] Some authors further suggest that in the U.S. longevity among some low SES groups, as measured by education, declined not just relative to high SES groups, but also in absolute terms. Olshansky et al. (2012, p. 1808), for example, claim that "along the educational and socioeconomic status gradient, those at the top are gaining modest amounts of longevity, but whites at the bottom are losing ground at a faster pace—that is, they are either experiencing a decline in life expectancy or a slower rate of increase relative to those at the top." The evidence for these claims stems largely from comparing mortality rates across categories of educational attainment over time.

However, at the same time that mortality rates conditional on education changed, the distribution of educational attainment in the U.S. also changed dramatically. Consider the data on the distribution of education for 25–84 year old women in 1984 and 2006 presented in Table 1. Between 1984 and 2006, the share with less than a high school diploma declined from 25.8 percent to 14.0 percent, suggesting that those with less than a high school diploma are relatively more disadvantaged in 2006 than in 1984. Attaining less than a high school diploma thus cannot serve as a stable marker of SES over time.

The changes in how education is distributed between 1984 and 2006 affect how one interprets observed changes in mortality by education over that same time period. The gap in five-year mortality between females with less than a high school diploma and those with more than a high school diploma increased by 1.3 percentage points between 1984–89 and 2002–06. This increase of 0.013 is the result of (i) an increase in five-year mortality among those with less than a high school diploma from 0.060 in 1984–89 to 0.065 in 2002–06, and (ii) a decrease in five-year mortality among those with more than a high school diploma from 0.044 to 0.036. However, because the population share with less than a high school diploma declined, we cannot be sure that outcomes in this group did not deteriorate simply because this group is increasingly negatively selected. By

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[1] The literature originates with Kitagawa and Hauser (1973). For a comprehensive recent overview, see Hummer and Lariscy (2011).

contrast, the share with more than a high school diploma increased from 31.7 percent to 45.8 percent, suggesting that this group has become less positively selected. Thus the decline in mortality in this group unambiguously indicates that mortality declined for those at the top of the education distribution.

As illustrated above, changes in the education distribution over time complicate attempts to draw conclusions about how mortality outcomes conditional on SES have changed. The fundamental question we address in this paper is how to infer whether the SES gradient in mortality has changed over time using data on education levels, given that the education distribution itself has changed so dramatically.

In order to draw conclusions about the SES-mortality gradient based on educational attainment, one needs to make strong assumptions on how SES maps into education, and potentially on how mortality is functionally related to SES. Typically, researchers in the literature on SES-mortality gradients do not make these assumptions explicit, but the conclusions drawn nevertheless crucially depend upon them. We explicitly define how SES maps into education and derive methods for testing whether the SES-mortality gradient changes over time using data on education and mortality, without imposing additional strong assumptions on the functional relationship between mortality and SES.[2] Regarding the mapping of SES into education, we assume that SES is a relative measure of position in a hierarchical social structure.[3] Further, we assume that education is a dominant marker of SES in the sense that SES is weakly increasing in education. These are clearly strong assumptions: social relations are too complicated to allow for strict hierarchical rankings, and education is just one of many markers of social status. Nevertheless, these assumptions (or similar ones) are implicit in numerous studies, such as Olshansky et al. (2012), that measure mortality differences conditional on education and then discuss SES gradients in mortality based on these measurements.[4]

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[2]It is possible to derive stronger results from the observed relationship between mortality and education if stronger restrictions on the relationship between SES and mortality are imposed. For instance, linearity assumptions relating mortality and SES would allow for exact estimation of the slope of the SES-mortality gradient using data on education and mortality given our assumptions on how SES maps into education. We do not impose such additional assumptions besides assuming that mortality weakly declines in SES.

[3]Dictionary.com defines socioeconomic status as "An individual's or group's position within a hierarchical social structure."

[4]Most of the literature uses educational attainment as the principal indicator of SES in order to examine socioeconomic differentials in adult mortality (see, for example, Hummer and Lariscy 2011; Olshansky et al.

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Using these two assumptions, and the assumption that mortality declines weakly in SES, we develop a new method to test how the relationship between mortality and SES evolves, while accounting for changes in the education distribution. The data directly inform us about (i) the share of the population in each education group, and (ii) mortality conditional on educational attainment. We propose a nonparametric test to assess whether the observed education shares and mortality rates at two points in time could be consistent with the same underlying relationship between SES and mortality. We then apply this test to data from the U.S. covering the period from 1984 to 2006. As detailed below, we confirm the standard conclusion that the gradient has increased for females. However, we fail to find evidence that the gradient has increased for males. This contrasts with a number of prior studies, including our own, that have found increases in the gradient for males (under stronger—typically parametric—specifications).

Our test works as follows. We assume that education is a dominant marker of SES. We can therefore associate observed education levels with a specific range of the SES distribution at a given time. Consequently, the education distribution implies a partition of the SES distribution, and we can estimate the mortality rate in each element of this partition (i.e., for each education group). Under the null hypothesis we can, without recourse to parametric assumptions, make basic predictions for how mortality rates in each element will change as the distribution of education shifts over time. In particular, if an education group shifts downward in the SES distribution, then the mortality rate for that group should increase relative to the population at large. For example, among females the segment of the SES distribution associated with 12 years of education in 1984–89 ranges from percentile 25.8 to percentile 68.4, whereas in 2002–06 it ranges from percentile 14.0 to percentile 54.2 (Table 1). Therefore, this segment shifted down in the SES distribution. Under the null, mortality should have increased in this segment relative to the population average. In this manner, we can construct a set of testable predictions for the null hypothesis that the SES-mortality gradient has not increased over time.

In practice, we implement our testing procedure separately for each gender using six

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2012). There are two main reasons for this. First, contrary to occupation and work-related measures of SES, education is available as a measure of SES for the retired, the unemployed, and those out of the labor force. Second, education is fixed throughout adulthood. Studies based on education are thus less vulnerable to issues of reverse causality (Preston and Taubman 1994).

education groups. Our proposed testing procedure thus amounts to a multiple one-sided hypothesis test for the mortality rates associated with the six different levels of education.[5] While multiple two-sided hypothesis tests are straightforward to implement using standard methods and software packages, multiple one-sided hypothesis tests of the type we are considering here are less straightforward. In Section 2.2 we adapt results from Kodde and Palm (1986) and Wolak (1989) to our context and thereby derive the required test statistics and critical values. When we implement this test on the 1984–89 and 2002–06 time periods, we fail to reject the hypothesis that the SES-mortality gradient has remained unchanged for males, but we do marginally reject the hypothesis of no change in the gradient for females. The failure to find evidence for a change in the SES-mortality gradient for males, however, could reflect a lack of power of our proposed test. We address this lack of power by considering another implication of our null model, which is that any combination of education groups that shifts *upward* in the rank distribution should have *lower* mortality. Nevertheless, we still fail to reject the null hypothesis that the gradient has not changed among males using this alternative test. By contrast, we strongly reject the null that the SES-mortality gradient among females remained unchanged between 1984–89 and 2002–06.

We are not the first to consider how changes of selection across education (or other categorical measures of SES) might affect measured health gradients. Wagstaff et al. (1991), for example, compared different methods of measuring socioeconomic inequalities in health.[6] Their work supports the use of the Concentration Index (CI). When categorical variables are used to partition the support of the SES distribution, as in the case of education, then the literature refers to the between-group CI. However, these vary when the shares of individuals in the different categories vary, even if the underlying relation between SES and the health outcome is unchanged. The reason is that to compute the between-group CI, one assumes that health is constant with respect to socioeconomic

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[5]Our analysis considers three time periods rather than only the two time periods discussed in the introduction. Table B1 presents the information analogous to Table 1 for the full set of education intervals, both genders, and all three time periods.

[6]Dowd and Hamoudi (2014) also discuss the issue of selectivity in a critique of the literature and Olshansky (2013) acknowledges the problem. These papers do not propose specific analytic approaches to overcome the issue.

rank within each category.[7] As a consequence, the between-group CI can indicate that socioeconomic inequalities in health change just because the distribution of education has changed. Our approach is designed to test for changes in socioeconomic differences in health while allowing for changes in selectivity.

A more limited approach could abandon the attempts to conceptualize SES and its relationship to educational attainment. Then our test would be interpreted simply as assessing whether observed changes in mortality rates conditional on education might be explained entirely by changes in selectivity into education groups. However, this would not address the broader question of inequality, which motivates much of the literature in this area. We think it is useful to formalize the notion of SES and its relationship to education given this emphasis in the literature, in part because it forces us to clarify the assumptions that are implicitly used to interpret differences in mortality rates conditional on some marker of SES as being informative about inequality.

As a final substantive point, we wish to comment on which part of the support of the SES distribution seems to be responsible for the strong rejection of the null hypothesis among females between 1984–89 and 2002–06. Visually examining the mortality rates over the education distribution, we find that the strongest suggestive indication against a stable SES-mortality gradient comes from the very bottom of the distribution. Mortality differences between those with a high school diploma only and those with greater educational attainment have remained relatively stable (in absolute numbers) since the 1980s, although there is some indication of an increasing difference between those with a high school diploma and those with a four-year college degree. But it is primarily at the bottom of the education distribution that we observe a widening in the relationship between mortality and education over time.

The remainder of the paper is structured as follows. Section 2 outlines an analytical framework and develops testing procedures for the relationship between SES and mortality. Section 3 describes the data used in this paper. Section 4 presents and describes the results of the statistical tests. Section 5 concludes.

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[7]See the discussion in Wagstaff and van Doorslaer (2004, page 298).

2 Analytical Framework

In this section we first model the latent relationship between an individual's socioeconomic status (SES) and her mortality rate. We then use this framework to develop nonparametric testing procedures to examine whether the relationship between mortality and SES has changed over time.

2.1 Mortality Model

The literature commonly uses education as the dominant marker of SES (e.g., Preston and Taubman 1994; Hummer and Lariscy 2011; Olshansky et al. 2012), and we follow this approach. To begin, we define SES directly as an individual's relative position within society.[8] Accordingly each individual, i, is associated with a rank, $r_i \in [0, 1]$, which expresses her SES.[9] The exact rank of an individual is unobserved, but we do observe their level of educational attainment, e_i. Because we take education to be the dominant marker of SES, we suppose there is a monotonic relationship between education and SES.[10] We state this formally with the following assumption.

Assumption 1 (Education as dominant marker) *The relationship between the discrete levels of educational attainment and the continuous values of latent socioeconomic status is monotonic: $r_i < r_j \Rightarrow e_i \leq e_j$ and $e_i < e_j \Rightarrow r_i < r_j$.*

This assumption implies that the observed education distribution partitions the latent SES distribution in the population. Denote by K the number of different levels of educational attainment observed in the data. Based on these categories we can define a partition of the SES distribution.

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[8]A thorough discussion of the concept of SES is well beyond our scope. Some notion of relative position appears in most definitions. See Oakes and Rossi (2003) for an interesting review and discussion of issues in defining and measuring SES in research on health outcomes.

[9]Naturally SES may depend on multiple attributes. The existence of a well defined ranking assumes these attributes can be collapsed into a single index.

[10]Which way the causation runs between SES and education is irrelevant for our purposes. We only require that education is an accurate marker of SES in the sense that those individuals with higher education are understood to be of higher SES. Of course if there are multiple attributes behind SES then it need not be monotonic in education. We make this simplifying assumption to facilitate the analysis, and leave for future research the possibility of extending our approach to multiple attributes.

Definition 1 (Education partition) *An education partition, $P_t \in [0,1]^{K+1}$, is a vector at time t with $K+1$ increasing thesholds p_t^k in the distribution of SES, where $p_t^0 \equiv 0$, $p_t^K \equiv 1$, and $k = 0, \ldots, K$.*

$$P_t = (p_t^0, p_t^1, \ldots, p_t^K)$$

For example, the vector associated with the education distribution for females in 1984–89 in Table 1, column 2 is $P_{1983-88} = (0, 0.258, 0.684, 1)$.[11]

We measure mortality as the probability of death over a five-year time period, t.[12] This is a function of the individual's SES, education, and age, a_{it}, and the function can change over time to reflect both overall changes in mortality and possible changes in the gradient. To define the function, let D_{it} be an indicator for whether individual i dies during period t; then the mortality function can be expressed as follows.

Definition 2 (Mortality function) *A mortality function $m_t(\cdot)$ gives the probability of death during period t conditional on SES (r), educational attainment (e), and age (a).*

$$m_t(r, e, a) \equiv \Pr(D = 1 \mid r, e, a, t)$$

We use this function to formalize the notion of a change in the gradient, which involves changes in this function other than a parallel shift.

Assumption 1 implies that SES fully determines education. Accordingly there is no variation in education conditional on SES that might be used to separately identify the effects of education and SES. Therefore, to proceed with our analysis, we subsume any independent effect of education on mortality in the effect of SES on mortality and write the mortality function as $m_t(r, e, a) = m_t(r, a)$.[13] Additionally, throughout the empirical

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[11]For this vector, $K = 3$. The corresponding vector associated with the education distribution for females with $K = 6$, for which the data is shown in Table B1, is $P_{1983--88} = (0, 0.122, 0.257, 0.683, 0.819, 0.942, 1)$.

[12]All subsequent references to an individual's "mortality rate" or their "probability of death" refer to the probability of death within a five-year time period.

[13]This is clearly not an innocuous assumption. For example, it is possible that education has a direct causal effect on mortality by enabling individuals to comprehend medical advice or by leading them to make better health decisions (Kenkel 1991; Lange 2011). The strength of such a link between education and mortality might vary over time. By assuming education to have no independent effect, we focus attention on the relative aspects of individuals in society, not their overall education. If the functional role of education in producing health changes over time, then this will be interpreted by us as a change in the SES gradient. Education is of course a determinant and marker of SES and therefore changes in the functional role of education do indeed reflect changes in the SES gradient. In this sense, our interpretation is correct.

analysis we fully adjust for age. Thus, for the remainder of the exposition, we will also keep age implicit and write $m_t(r)$.[14]

Assumption 2 below restricts the mortality function to weakly decrease in SES.

Assumption 2 (Monotonicity of mortality function) *Mortality weakly decreases in SES:* $r_i > r_j \Rightarrow m_t(r_i) \leq m_t(r_j)$.

Together with Assumption 1, this implies that mortality declines with education. The evidence presented in Section 3.2 provides strong support for this observable implication of the two assumptions.

We are interested in discovering how $m_t(r)$ changes over time. The problem in answering this question is that we cannot observe an individual's rank, r, so we cannot estimate the function $m_t(r)$ directly. However, we can calculate the mortality rate for each interval defined by the education partition. In our framework this is expressed as follows:

$$M_t^k = \frac{\int_{p_t^{k-1}}^{p_t^k} m_t(r) \, dr}{p_t^k - p_t^{k-1}}, k = 1, \ldots, K.$$

The mortality rate conditional on education approximates the underlying mortality function, $m_t(r)$, as a step function. This is illustrated in Figure 1.[15] For example, consider the middle group in Figure 1. For that group, we know that r lies between 0.3 and 0.7, and we observe a five-year mortality rate of 5.5 percent. The unobserved relation between mortality and r over this segment ranges from approximately 4.5–7 percent.

2.2 A Nonparametric Test for Increases in the SES-Mortality Gradient

Based on the model above, we develop and implement nonparametric tests of the hypothesis that the gradient of the relationship between SES and mortality has remained unchanged between two time periods t_1 and t_2. The alternative hypothesis is that the gradient has increased over time in some arbitrary fashion.

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[14]This expression of mortality as a function of a ranking in terms of a socioeconomic variable is similar to the Concentration Curve discussed by Wagstaff et al. (1991). The Concentration Curve, $S(r)$, is equal to the integral over the survivor function: $S(r) = \int_0^r (1 - m(s)) \, ds$.

[15]Figure 1 is not based on real data and is for illustrative purpose only.

While we test that the gradient of the relationship is constant, we do allow for a common shift of the mortality function over time. We could accommodate such a shift using either an additive or multiplicative time-varying term, g_t, in the mortality function. Under the null, the remainder of the mortality function is constant over time. Hence we formulate the null hypothesis as either:

$$H_0 : m_t(r) = \overline{m}(r) + g_t \qquad \text{or} \qquad H_0 : m_t(r) = \overline{m}(r) \cdot g_t \tag{1}$$

The "gradient" therefore corresponds to the function $\overline{m}(r)$. An increase in the gradient means that the slope of this function weakly increases over its entire domain, with a strict increase over some subset of nonzero measure.

In what follows, we focus on the additive case above.[16] The null hypothesis implies that the mortality function at times t_1 and t_2 should be identical once we remove a constant term from each period; i.e.,

$$m_{t_1}(r) - g_{t_1} = m_{t_2} - g_{t_2} = \overline{m}(r) \tag{2}$$

Therefore, we proceed by using mortality functions that are *demeaned within each time period*.[17]

Because the mortality rates at exact ranks r are unobservable, we must work with the average mortality rates for each interval defined by the education partition. To derive a testable implication from the model, we first identify those elements of the partition where the intervals in the distribution of SES shift downward from one time period to the next. These are intervals $(p_{t_1}^{k-1}, p_{t_1}^k)$ and $(p_{t_2}^{k-1}, p_{t_2}^k)$ such that $p_{t_2}^{k-1} < p_{t_1}^{k-1}$ and $p_{t_2}^k < p_{t_1}^k$. Then from the monotonicity of $m(r)$ we have the implication that

$$(p_{t_2}^k - p_{t_2}^{k-1})^{-1} \int_{p_{t_2}^{k-1}}^{p_{t_2}^k} \overline{m}(r)\,\mathrm{d}r \geq (p_{t_1}^k - p_{t_1}^{k-1})^{-1} \int_{p_{t_1}^{k-1}}^{p_{t_1}^k} \overline{m}(r)\,\mathrm{d}r \tag{3}$$

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[16]It is simple to extend our methodology to the multiplicative case by taking the log of the mortality rates.

[17]To see how demeaning within each time period yields mortality functions that will be the same across time periods, note that the overall average mortality rate in period t is $\int_0^1 m_t(r)\,\mathrm{d}r = g_t + \mu$, where $\mu \equiv \int_0^1 \overline{m}(r)\,\mathrm{d}r$. Subtracting this from $m_t(r)$ yields $\overline{m}(r) - \mu$, and we can set $\mu = 0$ without loss of generality.

In words, an interval that shifts downward over time would have increasing mortality (in the demeaned mortality function). For example, one can see in Figure 1 that if the intervals were to shift left the mortality rate would increase within each interval. The exact magnitude of this increase is unknown without knowledge of the underlying mortality function; we only know that the mortality rate must increase. Thus the model yields a one-sided null hypothesis of weakly increasing mortality for each interval that shifts downward over time.

Because this downward shift occurs for multiple education groups, the model yields a joint one-sided prediction under the null hypothesis. The alternative is that mortality decreases for one or more of these groups (relative to the overall mortality rate in each period), even though their intervals shift downward in the distribution of educational attainment. In the data, we observe in most cases that all K groups in the education partition shift downward over time. Thus the null hypothesis states that the vector of changes in the demeaned mortality rates for the K education groups lies in the positive orthant of $\mathbb{R}^K$. This null is tested against the alternative hypothesis that the vector of changes lies somewhere in the remainder of the space (i.e., some of the changes are negative). Tests for such hypotheses are developed in Kodde and Palm (1986) and Wolak (1989) and are closely related to multiple one-sided tests with point-valued nulls (e.g., Kudo 1963; Gouriéroux et al. 1982). The Wald statistic for these tests uses only those elements of the vector that violate the null, and these are standardized by the inverse of their variance matrix as in a typical Wald statistic for a two-sided test. The null distribution of this test statistic is a mixture of chi-squares, one for each possible number of violations, where the mixture weights are the probability of that number of violations. As suggested in Wolak (1989), we compute these weights via simulation using the estimated variance matrix for the vector of mortality changes among all groups. (Additional detail is provided in Section A.)

To compute the test statistic we need the mortality rate (after demeaning mortality across the whole population within each period) for each partition element k in time periods $t = 1$ and 2. These mortality rates are standardized to the joint population distribution of age, race, and region in 2000, as noted in Section 3. We recover the demeaned mortality

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rates and their joint variance matrix using a dummy variable regression that includes a constant term for each time period, μ_t, and constrains the coefficients on the indicators for the K education groups to add to zero:

$$D_{it} = \mu_t + \sum_{k=1}^{K} \beta_t^k \mathbb{1}(k_i = k) + u_{it}, \qquad t = 1, 2 \tag{4}$$

where in each period t the sum of the β_t^k weighted by the share of individuals in group k is constrained to be equal to zero (i.e., $\sum_k \beta_t^k (p_t^k - p_t^{k-1}) = 0$, $t = 1, 2$), and u_{it} is a mean-zero error term.[18] The variance matrix estimate is robust to heteroskedasticity and clustered on the individual in cases where an individual appears in multiple time periods.

2.3 Augmented Test With Upward Shifts

It is possible that our test has weak power against certain violations of the null hypothesis, particularly from changes in the gradient toward the bottom of the education distribution. Therefore, we consider an alternative version of the test that has greater power to detect such changes in the gradient.

To explain this test, note that in its simplest form, an increase in the gradient would be represented as a rotation of a linear relationship, as shown in Figure 2. Here it is apparent that the power to detect such a change with the above test comes from the top of the education distribution, which is to the right of the intersection of the two underlying mortality functions (the dotted lines). Only to the right of the intersection is it possible that the mortality rate in an interval might have declined even though the interval shifted downward (i.e., the gray line that runs from the 60th to 100th percentile). Thus, violations of the null could only be detected toward the top of the education distribution. We could increase the power of our test against alternatives such as that represented in Figure 2 by reconfiguring the education partition in an appropriate fashion. In particular, we could combine intervals in the later years so that we obtain upward shifts in intervals at the bottom of the education distribution. Under the null, any segment that shifts upward should have lower mortality. Accordingly for the alternative test we create an interval that

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[18]Note that u_{it} has only two points of support because $D_{it} = 0$ or 1; i.e., this is a linear probability model.

shifts upward over time by combining the lowest groups in the education partition in the later time period. Then the full prediction under the null is that mortality should increase for those intervals that shift downward but should decrease for those intervals that shift upward over time. Figure 2 indicates how we would find evidence against the null if there was an increase in the underlying gradient, as is illustrated here. In this example, it is clear that if the lowest two education groups were combined in the second period, that combined group would shift upward in the education distribution but would also have higher average mortality relative to the single lowest group in the first period.

When we implement this test in our data, we compare the lowest interval in the first period with the combination of the lowest two intervals in the second period. For example, we combine the bottom two intervals in 2002–06 in Figure 3 below, which then extends beyond the lowest interval in 1992–96 and (barely) beyond the lowest interval in 1984–89. We use only this single combination of the first and second elements because the third element, grade 12, is a large group that reaches the middle of the distribution, while the power to detect violations in this manner is likely to come from the bottom of the education distribution. We also include the top interval in this test, which shifts downward and therefore is predicted to have increasing mortality.[19]

3   Data

3.1   Sample Description

Our data come from two sources: the National Longitudinal Mortality Study (NLMS) Public Use Microdata Sample (PUMS) and the National Health Interview Survey (NHIS) linked to the National Death Index (NDI).[20] The NLMS consists of data from Current Population Surveys in the early 1980s and a subset of the 1980 Census combined with

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[19]We only use the top interval, not the top two, because it is unlikely that the intersection between the two underlying mortality functions in some alternative hypothesis would be this high in the SES distribution. Accordingly we may have better power against such alternatives by only using the top interval.

[20]Information on the NLMS is available at: `https://www.census.gov/did/www/nlms/index.html`. Information on the NDI is available at: `http://www.cdc.gov/nchs/ndi.htm`. Information on the NHIS linked mortality files is available at: `http://www.cdc.gov/nchs/access/data_linkage/mortality/nhis_linkage.htm`.

death certificate information. The NHIS sample covers respondents to the NHIS from 1986 to 2000 which have been linked to deaths recorded by the NDI through 2006.[21] The NLMS and NHIS are particularly useful since educational attainment is self-reported during the year the individual is interviewed in the base sample. This removes the need to rely on education as recorded on death certificates. Education data from death certificates is often missing and is known to be subject to nonrandom measurement error (Sorlie and Johnson 1996). Furthermore, data in the NHIS is gathered during face-to-face interviews, which reduces (but does not eliminate) exaggerated claims of educational attainment (Black et al. 2003).

We restrict our analysis to non-Hispanic blacks and whites between 25 and 84 years old.[22] Following Cutler et al. (2011), we restrict the analysis to individuals surviving at least one year from the baseline interview. This is necessary since the base samples do not include the institutionalized population, which includes those in nursing homes. The concern is that the institutionalized have higher death rates than the rest of the population. Conditional on surviving one year, mortality rates for the institutionalized population closely resemble those for the entire population (Meara et al. 2008). All mortality rates are standardized to the age, race, and Census region distribution in the NHIS survey in 2000 and are calculated separately by gender, so that trends do not reflect changes in the distribution of these characteristics.[23]

We use our two data sources to estimate mortality rates in three 5-year time periods, which allow us to analyze trends in mortality by SES rank over time. Our construction of the three mortality time periods is summarized in Table 2. All records in the NLMS are assigned a common starting point of April 1, 1984. We calculate mortality rates by identifying those in the sample who died during the subsequent 5-year period. The precise mortality time period is April 1, 1984 to March 31, 1989, which we abbreviate as 1984–89. We construct two 5-year mortality time periods from the NHIS: from January 1,

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[21]Linked mortality data to NHIS surveys are available from the date of NHIS interview through the last quarter (October–December) of 2006.

[22]Age was top-coded at 85 years in the NHIS from 1997 onward, so we restrict to a maximum of 84 years of age in order to include individuals from the more recent survey years.

[23]Montez and Berkman (2014) find subtle differences by region in trends in the education-mortality gradient.

1992 to December 31, 1996, and from January 1, 2002 to December 31, 2006. For the former time period we pool the annual interview samples from 1986 to 1990, and for the latter we use all available interview samples from 1986 to 2000. Our three constructed samples all consist of individuals who are alive at the start of their respective mortality time period.

Prior to 1992, the CPS asked for the highest grade level a respondent had attended, and a separate question verified whether the respondent had actually completed that grade. In the NLMS, grade levels are grouped at lower levels; categories include grade 1 through grade 4, grade 5 and grade 6, and grade 7 and grade 8. Grades 9 through 6 years of post-secondary education are available year-by-year.

From 1986 to 1996, educational attainment in the NHIS was measured as the highest completed year of schooling ranging from 1 year of schooling to 18 or more years of schooling. From 1997 to 2000, the concept used to measure educational attainment changed to an *educational achievement* approach, using a combination of years of schooling as well as specific degrees attained such as "some college but no degree," "associate degree," and "bachelor's degree." The highest completed year of schooling ranges from 1 year of schooling to 12 years of schooling, followed by a range of post-secondary options. We recoded the post-secondary options as follows: some college but no degree = 13 years of schooling; associate degree = 14 years of schooling; bachelor's degree = 16 years of schooling; master's degree, professional degree, or doctoral degree = 18 years or more of schooling.

For the main analysis we divide the population into six groups by educational attainment. These groups are: individuals who completed up to grade 8; those who completed grade 9 through grade 11; those who completed grade 12; those who completed some college (1-3 years, with or without an associate degree); those who completed 4 years of college; and those with more than 4 years of post-secondary education.

3.2 Education and Mortality Rates: The Raw Data

Table B1 displays the 5-year standardized mortality rates (by age, race, and region) and the population shares in each education group and in each time period. The same information is displayed graphically in Figure 3 for males and Figure 4 for females. In the discussion

that follows we refer to the statistics given in Table B1 and displayed in these two figures.

Figure 3 shows male mortality by percentiles of educational attainment for the three samples from different time periods defined in Table 2. There are six education groups that partition the distribution of educational attainment. The share of the population in each education group corresponds to the length of the horizontal line segments. For instance, we observe that the share of males with more than 4 years of post-secondary education increased slightly from 10.5 percent in 1984–89 to 11.4 percent in 1992–96 and finally 12.0 percent in 2002–06. The average mortality rate for each group is represented on the vertical axis. For example, we see that the average mortality of males with more than four years of post-secondary education fell relatively slowly from 0.055 to 0.049 between the 1980s and 1990s and then decreased more rapidly to 0.036 between the 1990s and 2000s.

Figure 3 illustrates three findings regarding the relation between mortality and education over time. First, mortality declined rapidly over the last three decades across the education distribution. Second, there are large disparities in mortality by education and these disparities persist over time. A third finding apparent from Figure 3 is that mortality in both absolute and relative terms declined more for males at the top of the education distribution. Between 1984–89 and 2002–06, mortality rates among those with more than four years of college decreased by 1.9 percentage points from a base of 5.5. Furthermore, they decreased by 1.8 percentage points among those with exactly four years of college. By contrast, over the same time period the mortality rates among those in the lowest two education groups declined by only 1.2 percentage points in both cases.

Figure 4 mirrors Figure 3 but for females. As for males, we find that there are large disparities in mortality by education in all three periods. However, there are several striking differences between females and males. First, while average female mortality by educational attainment is substantially lower than for males, female mortality has declined less between the 1980s and 2000s. Second, the declines in female mortality were much more concentrated among women at the top of the education distribution. Indeed, mortality rates among the least educated women seem to have increased between 1984–89 and 2002–06. By contrast, among males mortality rates declined at all levels

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of educational attainment. We cannot be sure, of course, whether the increase in the mortality rates among the least educated women simply reflects the shift down in SES associated with these education groups. This is the question we address next with the results from our testing procedure.

4 Results

In Figures 5 and 6 we show male and female mortality functions for 1984–89 and 2002–06 with 95 percent confidence intervals. The mortality functions in both periods have been demeaned and therefore average to zero within each period. These figures represent the mortality functions we use to implement our testing procedures.

We can compare the mortality functions between the two time periods in each figure to see which segments of the education partition violate the null. Such a violation occurs if a segment that shifts downwards (to the left) in the education distribution has lower mortality in 2002–06 than in 1984–89. For males none of the education groups violates the prediction under the null; instead all segments show higher (demeaned) mortality in 2002–06. Thus we find no evidence for an increase in the SES-mortality gradient among males using our first testing procedure. Correspondingly, Table 3 reports that the test statistic for males between 1984–89 and 2002–06 is 0. Comparing the 1990s with the 2000s does yield a violation of the null, but the test statistic for this comparison is much smaller than the critical value. For females, we observe in Figure 6 that mortality declined among the top two education groups from 1984–89 to 2002–06 despite these segments shifting downward in the education distribution. This decline in relative mortality was fairly substantial for females with exactly four years of education. Nevertheless, the test statistic for the basic test applied to this time span is marginally below its critical value (see Table 3). On the other hand, the statistic from the test comparing 1992–96 to 2002–06 is marginally above its critical value, thereby formally rejecting the hypothesis of no change in the gradient for females over that time span. The top panel in Table 3 thus reveals weak evidence that the gradient increased among women and no evidence that it increased among men.

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Figure 6 illustrates why our first test could be underpowered in detecting changes in the mortality gradient. The mortality rates in the two lowest groups, grade 8 and under and grade 9–11, are much higher relative to the population average in 2002–06 than the mortality rate in the lowest group, grade 8 and under, in 1984–89. However, since these segments shifted downward, this substantial increase in relative mortality among the least educated can be explained as resulting either from a change in the SES gradient or from a change in selectivity associated with education. Therefore, it does not contribute to the test statistic and will not be detected by our first test. Since the first test exclusively relies on segments that shift left and for whom relative mortality declined, it is not well designed to detect changes in the gradient that manifest themselves as relative increases in mortality at the bottom of the distribution. It is this lack of power that the augmented test described in Section 2.3 is designed to address. The augmented test combines segments at the bottom of the partition to obtain additional testable implications from upward shifts in the education distribution. Using the augmented test we strongly reject the absence of a widening of the SES-mortality gradient among females from 1984–89 to 2002–06 (see Table 3). Among males, however, we still fail to reject the null of no change in the gradient, both for the full time span and each shorter time span. Thus our results provide strong evidence that the SES-mortality gradient widened among females over the last thirty years, even once changes in the distribution of educational attainment are accounted for. By contrast, among males any evidence that the SES-mortality gradient increased over this time is marginal at best. Our tests do not identify where in the SES distribution the change in the gradient among females is occurring. However, visual inspection of Figure 6 strongly suggests that the increase in the gradient among females is driven more by changes at the bottom of the SES distribution than at the top. It appears that the widening of the SES-mortality gradient among females has been driven primarily by the smaller gains in mortality among the least educated.

5 Conclusion

The evolution of inequality increasingly holds a central place in societal discourse. In recent years this fact has been demonstrated by the rise of the "Occupy" movement, which dominated headlines in late 2011, and by the tremendous success of Thomas Piketty's *Capital in the Twenty-First Century* (Piketty 2014). Within this context, the finding that the mortality difference between the least and the most educated has increased substantially since the 1980s has seemed to strike a nerve. It has generated substantial interest both in academic circles and in the popular press (e.g., Tavernise 2012). Finding an increasing mortality-education gradient reinforces the perception of an increasingly polarized, unequal society. If mortality inequalities in the population widened substantially, then it is possible that the less well-off did not just fail to benefit from the increase in material wealth over the last few decades, but they might also have failed to benefit from the tremendous progress made in reducing mortality. The question of whether mortality inequality increased in the population is thus of primary importance for understanding broader social trends.

In this paper, we ask whether evidence that the mortality-education gradient has increased can be taken as evidence that mortality inequality associated with underlying socioeconomic status has widened as well. Our contribution is to ask critically whether the evidence based on the mortality-education gradient is informative about the relation between mortality and SES *once one takes into consideration that the education distribution itself has shifted tremendously over the last few decades*.

Our approach relies on the assumption that education is a dominant marker of SES—a restrictive assumption albeit one that is implicit in much of the literature. Beyond this, we impose only minimal assumptions on how mortality and SES are related, namely in that we assume mortality decreases weakly with SES. From this starting point, we derive two testing procedures of the null hypothesis that the SES-mortality gradient has remained constant over time. We implement these tests using data from 1984–89, 1992–96,and 2002–06.

Our results are mixed. It is difficult to establish firm evidence that the SES-mortality gradient has increased among males. A simple visual inspection of Figure 3 shows

why this is the case: for males, mortality decreased among all education groups in a fairly stable and regular manner. Thus we find little evidence that mortality inequalities increased among males between 1984 and 2006. On the contrary, we find strong evidence that the SES-mortality gradient increased among females using one of our two tests. This evidence stems largely from the lack of progress in reducing mortality rates at the bottom of the education distribution, evident in Figure 4. Since 1984, mortality rates among the least educated women increased, and this increase is large enough and cuts across enough of the education distribution that it is difficult to explain as simply the result of increasingly negative selectivity. We therefore conclude that the SES-mortality gradient must have changed among females.

## Acknowledgments

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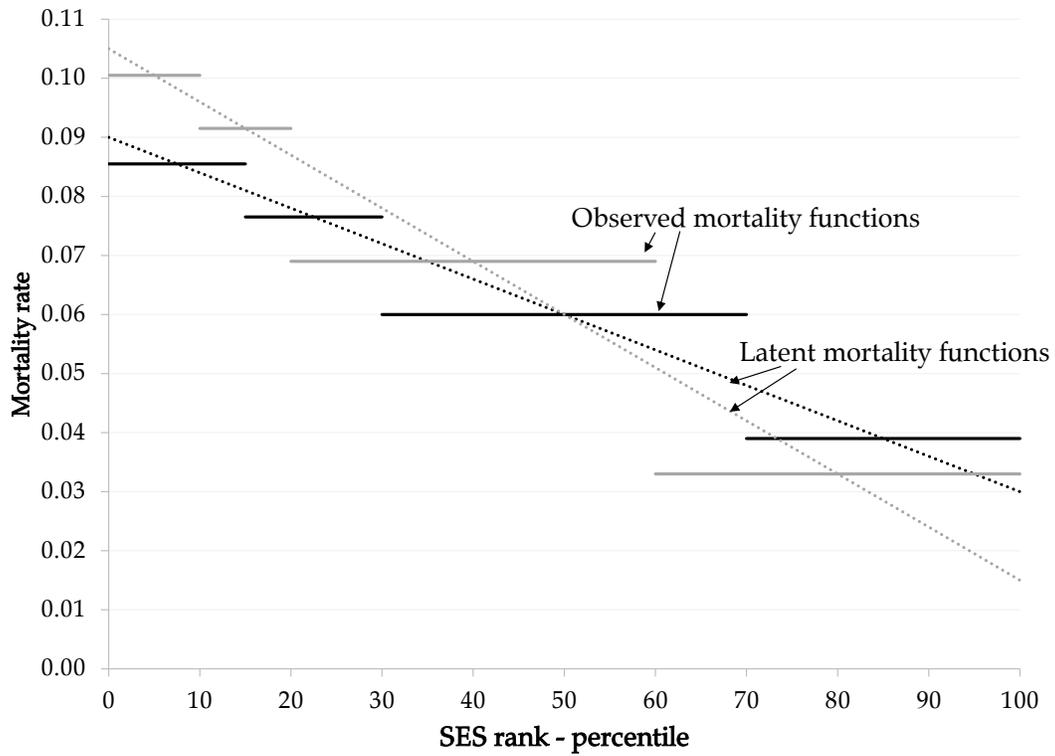
Figures & Tables

Figure 1: An illustrative example of a latent mortality function and an observed mortality function
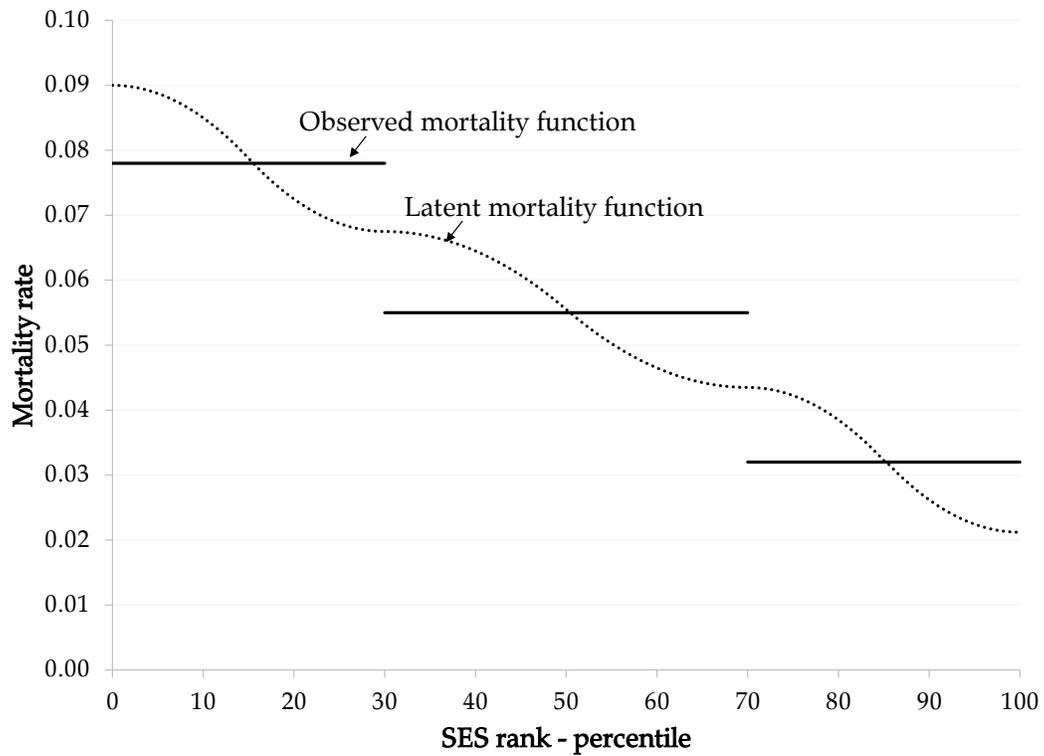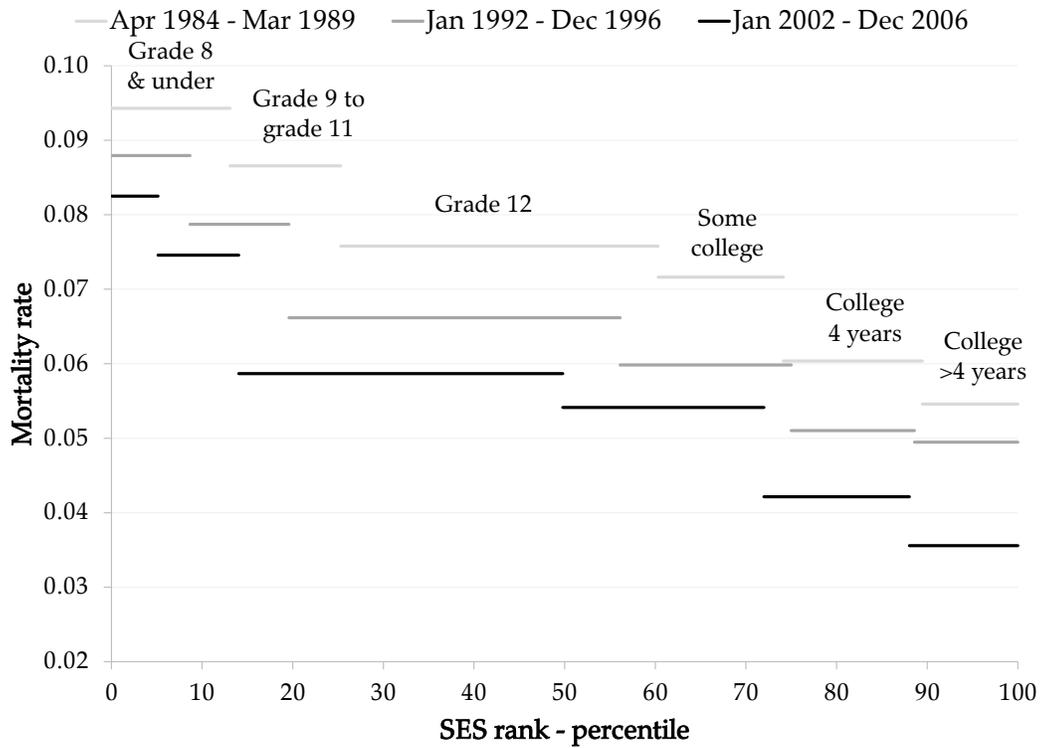

Notes: The data displayed in this figure are not based on real data and are for illustrative purpose only.

Figure 2: An illustrative example of a gradient that steepens over time

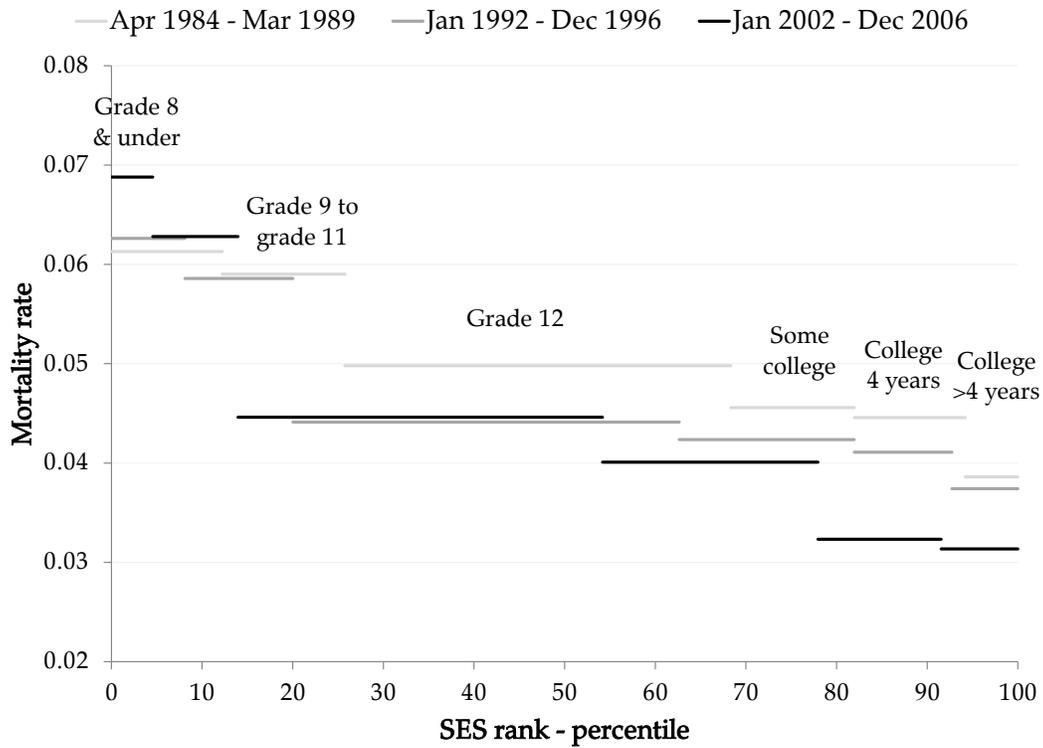*Notes:* The data displayed in this figure are not based on real data and are for illustrative purpose only.

Figure 3: Observed mortality rates by SES for males (1984–2006)

Notes: See the text for detail on the construction of the male mortality rates.

Figure 4: Observed mortality rates by SES for females (1984–2006)

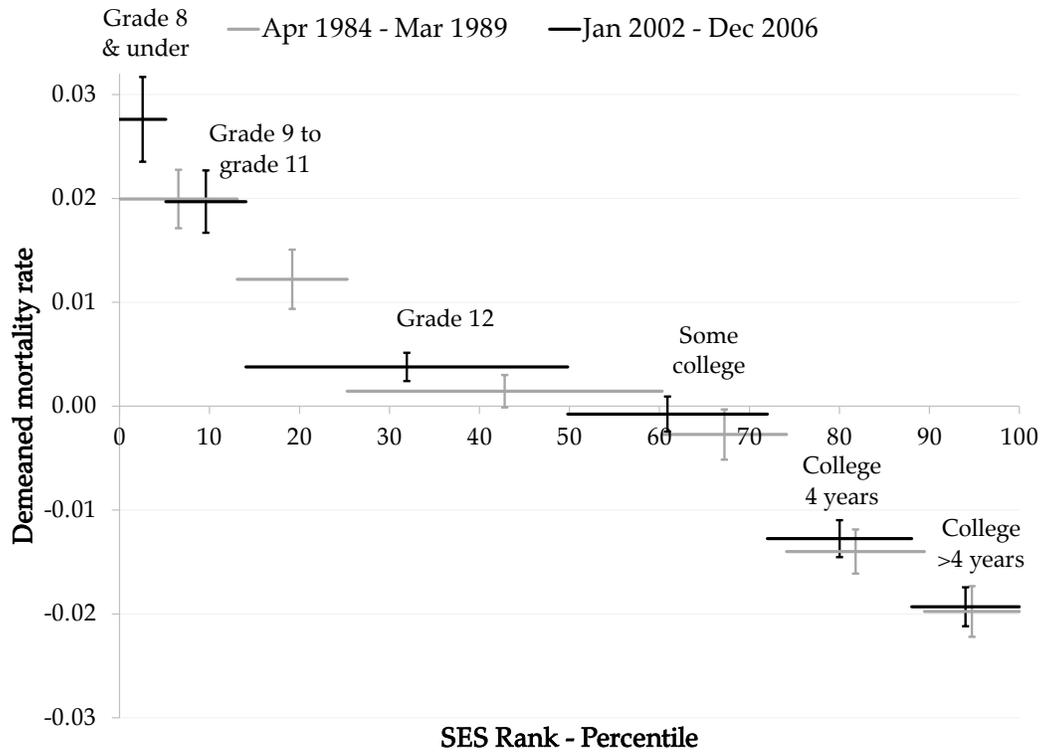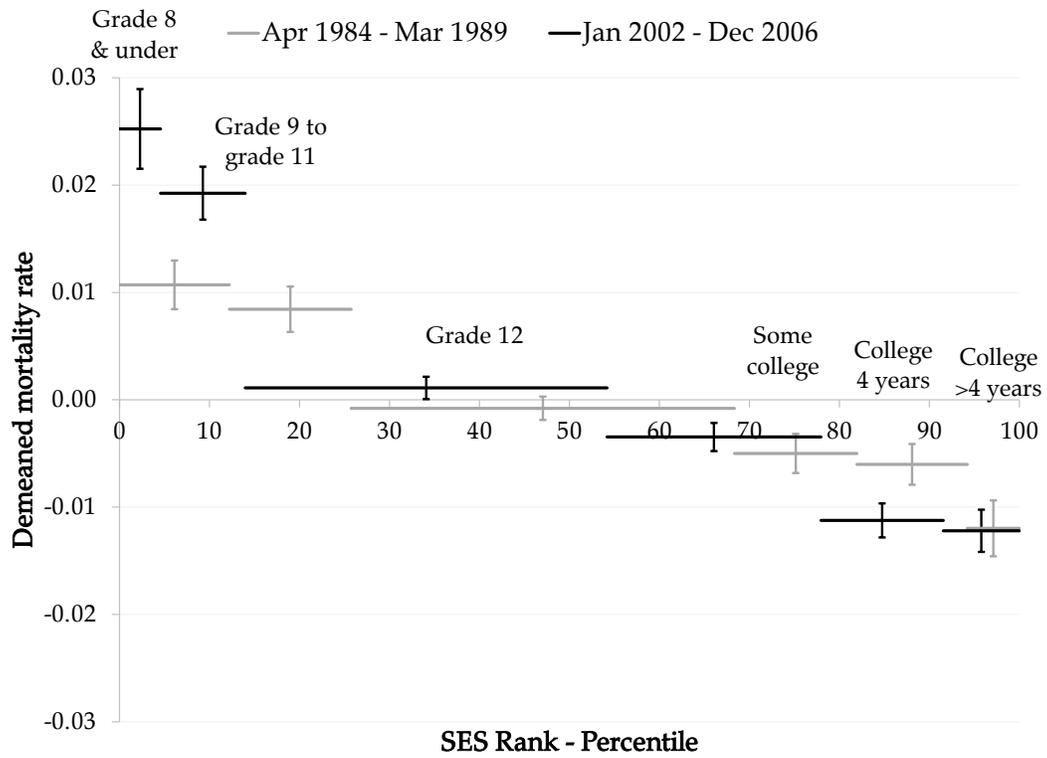*Notes:* See the text for detail on the construction of the female mortality rates.

Figure 5: Demeaned mortality rates by SES for males (1984–2006)

Notes: See the text for detail on the construction of the male demeaned mortality rates.

Figure 6: Demeaned mortality rates by SES for females (1984–2006)

Notes: See the text for detail on the construction of the female demeaned mortality rates.

Table 1: Female mortality rates by educational attainment and time period

Educational attainment	1984–89		2002–06	
	Population share	Mortality rate	Population share	Mortality rate
Less than grade 12	0.258	0.060	0.140	0.065
Grade 12	0.426	0.050	0.402	0.045
More than grade 12	0.317	0.044	0.458	0.036

Notes: These figures are calculated from the National Longitudinal Mortality Study and the National Health Interview Survey public-use Linked Mortality Files (see Section 3 for details). The mortality rate is the average probability of death within the 5-year time period at the top of the column (the period 1984–89 runs from April 1984 to March 1989, whereas 2002–06 runs from January through December). All statistics are standardized by age, race, and region to the distribution in the 2000 NHIS.

Table 2: Construction of mortality time periods by data source

Data source	Survey years	Mortality time period	Sample size
NLMS	Early 1980s	April 1, 1984 – March 31, 1989	674,539
NHIS	1986–1990	January 1, 1992 – December 31, 1996	280,666
NHIS	1986–2000	January 1, 2002 – December 31, 2006	686,645

Table 3: One-sided statistical test results

	Female			Male		
	1980s–1990s	1990s–2000s	1980s–2000s	1980s–1990s	1990s–2000s	1980s–2000s
Basic test using only decreasing education segments						
Statistic	1.72	8.80	8.16	0*	3.11	0*
{5% c.v.}	{8.26}	{8.25}	{8.23}	{6.34}	{8.21}	{8.20}
[*p*-value]	[0.604]	[0.040]	[0.051]	[0.977]	[0.376]	[>0.999]
Augmented test using a combination of increasing and decreasing segments						
Statistic	3.22	3.63	39.65	0*	3.11	1.53
{5% c.v.}	{4.28}	{4.27}	{4.27}	{4.25}	{4.26}	{4.27}
[*p*-value]	[0.088]	[0.070]	[<0.001]	[0.733]	[0.093]	[0.226]

Notes: c.v. is the critical value. The precise start and end dates of each time period are given in Table 2. *There were no violations of the null hypothesis in these comparisons, hence the value of the test statistic is zero by definition. However, the *p*-values are less than one because there is positive mass at zero in the distribution of the test statistic under the null.

A Test Statistic & Critical Values

In this appendix we provide further detail on how the test statistic is obtained and how we determine the critical values and p-values reported in Table 3. For the main test using only downward shifts in the education partition, we start with the full vector of differences in the demeaned mortality rates:

$$\left[\left(\hat{\beta}_{t'}^1 - \hat{\beta}_t^1\right), \dots, \left(\hat{\beta}_{t'}^K - \hat{\beta}_t^K\right)\right]$$

where t and t' are the first and second time periods, the superscripts indicate the partition elements, and $K = 6$ for the six education groups used in each period. Because all partition elements shift downward over time (except for males in the comparison from 1984–89 to 1992–96), the null hypothesis is $(\hat{\beta}_{t'}^k - \hat{\beta}_t^k) \geq 0$ for $k = 1, \dots, K$. The test statistic is like a typical Wald statistic, which multiplies elements of this vector of differences by the inverse of their variance matrix, but using only those elements that are negative and hence violate the null.

It is straightforward to construct the test statistic using the realized value of the vector $\left[\left(\hat{\beta}_{t'}^1 - \hat{\beta}_t^1\right), \dots, \left(\hat{\beta}_{t'}^K - \hat{\beta}_t^K\right)\right]$ and its estimated variance-covariance matrix. It is more difficult to obtain the null distribution of this statistic. Following Kodde and Palm (1986) and Wolak (1989), the null distribution of the test statistic is a mixture of chi-squares with zero to K degrees of freedom, which correspond to the number of possible violations of the null hypothesis in a K-dimensional vector. To understand this intuitively, note that under the null, it is possible to observe 0, 1, 2 or up to K segments for which $\left(\hat{\beta}_{t'}^k - \hat{\beta}_t^k\right) < 0$ even though the null holds. Thus, under the null, the test statistic is a mixture of K chi-squared random variables with degrees of freedom varying from 0 to K. The mixture weight on the χ^2 with exactly n degrees of freedom is given by the probability of observing exactly n violations if the true differences $\left(\hat{\beta}_{t'}^k - \hat{\beta}_t^k\right)$ are all exactly zero (i.e., on the boundary of the space for the null hypothesis). These probabilities of observing exactly $k = 0, 1, \dots, K$ violations are difficult to obtain in closed form and depend on the variance-covariance matrix of the estimated coefficients. We compute these weights via simulation as suggested in Wolak (1989). Accordingly we simulate draws from a K-dimensional multivariate normal with mean zero and variance matrix equal to the estimated variance matrix for the vector of differences, $\left[\left(\hat{\beta}_{t'}^1 - \hat{\beta}_t^1\right), \dots, \left(\hat{\beta}_{t'}^K - \hat{\beta}_t^K\right)\right]$ and then count the number of negative elements in each draw. The proportion of draws with exactly n negative elements is a close approximation to the probability that the test statistic would have the same number of violations under the null, and so these proportions serve as the weights in the mixture of chi-squares. Finally, the critical value is

determined as the threshold such that the weighted sum of the probability mass above this point in a series of chi-square distributions with 0 to K degrees of freedom equals the desired significance level. The p-values analogously give the weighted sum of the probability mass above the observed value of the test statistic.

For the augmented test we use the difference between the demeaned mortality rates in the lowest education group in the first period, $\hat{\beta}_t^1$, and the lowest two groups in the second period, $\hat{\beta}_{t'}^{1,2}$, along with the difference between the rates in the top education group in both periods. Thus the vector of differences has only two elements:

$$\left[\left(\hat{\beta}_{t'}^{1,2} - \hat{\beta}_t^1 \right), \left(\hat{\beta}_{t'}^K - \hat{\beta}_t^K \right) \right]$$

The null hypothesis is $\left(\hat{\beta}_t^1 - \hat{\beta}_{t'}^{1,2} \right) \geq 0$ for the first element because it shifts upward (notice that the order of t and t' has been reversed) and $\left(\hat{\beta}_{t'}^K - \hat{\beta}_t^K \right) \geq 0$ as before for the second element. We compute the mixture weights as before, but now simulating from a bivariate normal with the appropriate variance matrix.

B Additional Tables

Table B1: Average mortality rates by educational attainment and time period

Educational attainment	1984–89		1992–96		2002–06	
	Pop. share	Mortality rate	Pop. share	Mortality rate	Pop. share	Mortality rate
Panel A: Females						
Up to grade 8	0.122	0.061	0.081	0.063	0.046	0.069
Grade 9 to grade 11	0.135	0.059	0.119	0.059	0.094	0.063
Grade 12	0.426	0.050	0.426	0.044	0.402	0.045
Some college	0.136	0.046	0.193	0.042	0.238	0.040
College 4 years	0.123	0.045	0.108	0.041	0.136	0.032
College >4 years	0.058	0.039	0.073	0.037	0.085	0.031
Panel B: Males						
Up to grade 8	0.131	0.094	0.087	0.088	0.051	0.082
Grade 9 to grade 11	0.122	0.087	0.109	0.079	0.089	0.075
Grade 12	0.350	0.076	0.365	0.066	0.358	0.059
Some college	0.138	0.072	0.189	0.060	0.222	0.054
College 4 years	0.153	0.060	0.136	0.051	0.160	0.042
College >4 years	0.105	0.055	0.114	0.049	0.120	0.036

Notes: Pop. is population. The mortality rate is the probability of death within the 5-year time period at the top of the column. 1984–89 is April 1, 1984 to March 31, 1989. 1992–96 is January 1, 1992 to December 31, 1996. 2002–06 is January 1, 2002 to December 31, 2006. All statistics are standardized by age, race, and region to the distribution in the 2000 NHIS.

Table B2: Demeaned mortality rates by educational attainment and time period

Educational attainment	1984–89		1992–96		2002–06	
	Demeaned mort. rate	95% conf. interval	Demeaned mort. rate	95% conf. interval	Demeaned mort. rate	95% conf. interval
Panel A: Females						
Up to grade 8	0.011	[0.008, 0.013]	0.016	[0.012, 0.021]	0.025	[0.022, 0.029]
Grade 9 to grade 11	0.008	[0.006, 0.011]	0.012	[0.009, 0.016]	0.019	[0.017, 0.022]
Grade 12	−0.001	[−0.002, 0.000]	−0.002	[−0.004,−0.000]	0.001	[0.000, 0.002]
Some college	−0.005	[−0.007,−0.003]	−0.004	[−0.006,−0.002]	−0.003	[−0.005,−0.002]
College 4 years	−0.006	[−0.008,−0.004]	−0.005	[−0.008,−0.002]	−0.011	[−0.013,−0.010]
College >4 years	−0.012	[−0.015,−0.009]	−0.009	[−0.012,−0.005]	−0.012	[−0.014,−0.010]
Panel B: Males						
Up to grade 8	0.020	[0.017, 0.023]	0.024	[0.019, 0.029]	0.028	[0.024, 0.032]
Grade 9 to grade 11	0.012	[0.009, 0.015]	0.014	[0.010, 0.019]	0.020	[0.017, 0.023]
Grade 12	0.001	[0.000, 0.003]	0.002	[0.000, 0.004]	0.004	[0.002, 0.005]
Some college	−0.003	[−0.005, 0.000]	−0.004	[−0.007, −0.001]	−0.001	[−0.002, 0.001]
College 4 years	−0.014	[−0.016,−0.012]	−0.013	[−0.017,−0.010]	−0.013	[−0.015,−0.011]
College >4 years	−0.020	[−0.022,−0.017]	−0.015	[−0.018,−0.011]	−0.019	[−0.021,−0.017]

Notes: Mort. is mortality. The demeaned mortality rate is the probability of death within the 5-year time period demeaned by the mortality rate across the whole population within each period. 1984–89 is April 1, 1984 to March 31, 1989. 1992–96 is January 1, 1992 to December 31, 1996. 2002–06 is January 1, 2002 to December 31, 2006. All statistics are standardized by age, race, and region to the distribution in the 2000 NHIS.