

Increased mortality of white Americans and a decline in the health of cohorts born after World War II

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Abstract

I show evidence that recent increases in the mortality of white Americans are rooted in a decline in the health of cohorts born after World War II, relative to the trend for earlier-born cohorts. These cohort health differences are evident by the 1980s, suggesting recent mortality increases have deep roots which predate the opioid epidemic and recent economic distress. I identify the role of cohort health by imposing the impact of age on mortality to follow the log-linear, Gompertz form. This imposition yields the sharp, falsifiable prediction — strongly borne out in the data — that a decline in cohort health will result in changes in the slope of the age-profile of log-mortality at the same cohort in each year. That is, log mortality rates in each year between 1985 and 2015 exhibit slope changes centered at the 1946 cohort for white men and the 1949 cohort for white women — consistent with a health decline beginning precisely with those cohorts. The size of these slope changes imply that the average mortality rate of the 1960 cohort of white women has been 22 percent higher and that of men 37 percent higher, than they would have had health followed the trend for earlier-born cohorts. The cross-cohort decline in health appears remarkably widespread across the United States.

Keywords: mortality | cohorts | white Americans

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1 Introduction

Case and Deaton (2015) document a disturbing trend of increasing mortality among 45 to 54 year old non-Hispanic white Americans since 1999. The initial discussion of a possible cause focused on factors that changed between 1999 and 2012, such as the increasing availability of prescription opioids and heroin and changing economic conditions for those without a college degree. Subsequent research has suggested instead that the mortality increase may be due to cohort differences in health and disadvantage which predated the 1990s (Case and Deaton, 2017; Lleras-Muney, 2017; Masters et al., 2017; Zang et al., 2018). That is, white Americans born between 1958 and 1968 — and therefore aged 45 to 54 in 2012 — may be less healthy on average than those born between 1945 and 1955 — who comprised the 45 to 54 year old age group in 1999.

I provide additional support for the cohort-based explanation — building on past research in two dimensions. First, I use a transparent strategy to identify the role of cohort health differences which yields intuitive falsifiable predictions that are borne out in the data. Second, I identify the precise cohorts after which health began to decline. I show evidence that the health of cohorts of white men born after 1946 and white women born after 1949 progressively worsened until at least cohorts born in the mid-1960s. This information on the precise timing of the cohort health decline can be used to discipline the continued search for its underlying cause.

I identify the role of cohort separately from that of age and year by relying on the well-known log-linearity of mortality by age — known as Gompertz law (Gompertz, 1825; Chetty et al., 2016). Imposing this structure on the shape of age effects allows for the transparent identification, and potential falsification, of a decline in cohort health as changes in the slope of the age-profile of log-mortality. These slope changes will have a particular staggered structure by age, for example a decline in the health of cohorts born after 1946 will lead to a slope change at age 39 in 1985, age 49 in 1995, age 59 in 2005, and age 69 in 2015. The existence of such particular non-smooth non-linearities by age across years would be hard to attribute to other differences in the health environment unrelated to cohort.

I show that these sharp predictions regarding the shape of the log-mortality age profile are strongly borne out in the data. For example, Figure 1 shows the log mortality rate of white men for the 4 years listed above, along with estimated piecewise-linear models. In each year the age-profiles exhibit clear slope changes or “breaks” similar to the staggered

structure described above: at age 40 in 1985, age 48 in 1995, age 60 in 2005, and age 68 in 2015. This staggered location of slope changes by age corresponds to a nearly uniform location by cohort, with the estimated breaks at the 1944 cohort in 1985 and 2005, and at the 1946 cohort in 1995 and 2005. These example years are not unique. Estimation of piece-wise linear models of unknown location, using the structural break methodology of Hansen (1999, 2000) reveals strong statistical evidence that in all years between 1985 and 2015 a slope change exists and is located at or near the 1946 cohort. Similarly, for white women the change in slope is located at or near the 1949 cohort across all years.

Motivated by these reduced form patterns consistent with a decline in cohort health, I estimate models of log mortality including linear age effects in each year and a trend break in cohort effects. As suggested by the graphical patterns and within-year regressions, these models estimate a trend break in log mortality to occur at precisely the 1946 cohort for white men, and between the 1948 and 1950 cohort for white women. The trend break is also large: for example, the smallest estimate across specifications suggests that the 1958 cohort of white women has had on average approximately 22 percent higher mortality rates than they would have absent the trend break. Similarly, it implies that the 1956 cohort of white men had on average approximately 28 percent higher mortality rates than what would be predicted by the trend for preceding cohorts. These findings are also robust to the inclusion of higher-order polynomials in age — up to including a separate cubic-in-age in each year — validating the assumption of linearity against an alternative of smooth but non-linear age-effects.

The cohort-specific explanation can also explain the staggered timing of recent increases in mortality of different age groups. It explains the fact that white womens mortality rate at ages 35-44 began to increase in the early 90s, that of those age 45-54 in 1999, and that of those age 55-64 only in 2001 — unhealthy post-1949 cohorts drive mortality increases first at young ages and subsequently at older ages, as they age into different age bins. I perform a simple simulation exercise validating this intuition: the cohort-specific trend break model — without any other non-linear age-by-year interactions — can match this staggered timing for white women. The year-over-year pattern of the mortality rate of white men by age show less *prima facie* evidence of cohort effects, but the cohort-specific trend break model also fits these patterns relatively well for men.

The cross-cohort decline in health is remarkably widespread across the United States. The slope changes in all 4 census regions are of similar size, and are estimated to occur

within a few cohorts of the national turning point. Further, all 50 states have estimated trend breaks which are positive in magnitude and greater than .01 for women and men. Perhaps surprisingly, no obvious geographical patterns are apparent in the size of breaks across states. Finally, the health decline appears concentrated among non-Hispanic whites and a similar decline is not evident for Hispanics — in years after 1997 when its possible to distinguish. And I show some suggestive evidence that a similar health decline to that of white Americans is evident for black women, and women and men of other races, but not for black men.

My paper contributes to the broad literature in economics and social science on the identification of age, period, and cohort effects.¹ This so-called age-period-cohort identification problem is usually solved by imposing additive separability of each factor plus an additional, often ad hoc, restriction. This usual approach can feel like a “black-box” — with no methods to assess credibility and little attention to model fit. The key advantage of my alternative approach is that it yields falsifiable predictions which allow for intuitive overidentification tests. Of course my approach also imposes different assumptions to achieve identification — the credibility of which must be assessed in any given setting. While, the usual approach is unrestrictive with respect to the shape of the age, period, and cohort effects respectively; it precludes any interactions across these effects — for example the impact of age is assumed to be fixed across years. My approach is more restrictive in one dimension by imposing a parametric form on the age effects, but less restrictive in allowing this parametric impact of age to be different in each year. My approach may be useful in other economic applications. For example, it could be used to test for cohort differences in unobserved “skill” — in the context of Mincerian wage regressions in which the impact of experience is traditionally assumed to be quadratic (Mincer, 1974; Card and Lemieux, 2001).

In addition to Case and Deaton (2015), my paper contributes to a larger literature in demography documenting patterns in the all-cause mortality rate of white Americans.² Yang (2008) and Masters et al. (2014) emphasize the importance of a cohort-perspective and estimate additively-separable age-period-cohort models of mortality whose results suggest

¹See for example Deaton (1997), Heckman and Robb (1985), and Mason and Fienberg (2012) for methodological discussions; and Lagakos et al. (2018), Chay et al. (2014), and Aguiar and Hurst (2013) for recent applications in economics.

²A large literature also examines widening gaps in mortality by education level, see for example Meara et al. (2008), Olshansky et al. (2012), and Sasson (2016). My study differs from this literature, and follows Case and Deaton (2015), by focusing on an increase in the mortality rate of the aggregate population of white men and women of all education levels.

that mortality declines since 1960 are largely driven by cohort factors. Masters et al. (2017) and Zang et al. (2018) apply these standard models to more recent data and find evidence for an important role for cohort factors in recent mortality increases. As noted above, my approach to identifying cohort effects builds on the standard approach used in these papers, with the advantage that it yields falsifiable predictions. My result therefore adds additional credibility to these claims of an important role for cohort factors in recent mortality increases. I also identify more precisely the cohort at which the health decline appears to have begun.

The health decline across cohorts of white Americans that I document seems likely to have broad implications beyond the recent mortality increase. These cohorts are beginning to enter old age and their depressed health could increase health care spending, depress labor force participation, and impact the solvency of specific programs such as Medicare and Social Security.

Additionally, the precise timing of the cohort health decline that I document will be important in disciplining the search for its underlying cause. For example, the further development of the preliminary theory of “cumulative disadvantage” posited in Case and Deaton (2017) — in which worsening opportunities at labor market entry for whites with low levels of education triggers progressively worse outcomes, culminating in an increased likelihood of untimely death — must explicitly account for why these opportunities worsened for men born after 1946 and women born after 1949 in particular. Other potential explanations focusing on early-life factors such as maternal smoking or pollution exposure, must also be able to match this precise timing by cohort.

2 Data

I use vital statistics data derived from death certificates and population estimates from the Census Bureau to calculate mortality by single age and year.

In particular, I use the Multiple Cause of Death File from the Center for Disease Control and intercensal population estimates from the Census Bureau and the Surveillance, Epidemiology, and End Results (SEER) Program of the National Cancer Institute. Using these sources I calculate mortality and mid-year population by single-age, race, and sex. I then calculate crude death rates — the ratio of mortality over mid-year population — by single-age, race, and sex cells. I then define birth cohort as $year - age - 1$.

My main analysis considers the aggregate mortality rate of white males and females of the United States by single year of age. Hispanic-origin was not reported on death certificates in all states until 1997, and is therefore not consistently recorded in the Multiple Cause of Death File until that year. I therefore focus primarily on mortality rates for all whites, including Hispanics and non-Hispanics.

In some supplementary analysis, I consider mortality rates of Hispanic and non-Hispanic whites separately for 1997-2015. I construct these series by single age and year using an analogous approach and the same data source as described above.

In addition to national mortality rates, I construct estimates of the mortality rates of white Americans separately for each of the 50 states. These estimates allocate deaths based on the state of *residence* reported on death certificates. I again use intercensal population estimates from SEER as the denominator.

3 Evidence of cohort-specific trend breaks in log mortality

I show that the mortality rate of white men and women has deviated, in a way that is systematically related to cohort, from its usual log-linear relationship with age, the so-called Gompertz curve (Gompertz, 1825). In particular, in each year since 1985 those born after the 1946 cohort for men and 1949 cohort for women have higher log mortality rates than the Gompertz curve would predict.

3.1 Methodology

I use the structural break estimation and testing framework of Hansen (2000) to provide formal evidence of a break in the cross-cohort mortality trend.

Consider the following model of log-mortality:

$$\ln(mort_{apc}) = \beta_a^p a + \beta_c^p c + \delta^p \cdot (\gamma^p - c) \cdot 1_{c \geq \gamma^p} + \mu^p + \epsilon_{apc} \quad (1)$$

where a denotes age, p denotes period (eg. year), c denote cohort; and $\ln(mort_{apc})$ denotes the log-mortality rate of individuals age a , in period p , and from cohort c . The parameters

β_a^p and β_c^p represent linear trends in age and cohort, respectively, in each year. I then allow in each year for a trend break by cohort — thereby letting the affect of cohort have a piecewise linear form. The size of the trend break is represented by δ^p . The precise cohort at which the trend break occurs is treated as unknown and a parameter to be estimated, γ^p . μ^p is a year-specific intercept, and ϵ_{apc} is an orthogonal error.

Because age and cohort are perfectly collinear in each year of data the linear trends in age and cohort, β_a^p and β_c^p , are not separately identified. However, the following transformed model is identified:

$$\ln(mort_{apc}) = \tilde{\beta}^p a + \delta^p \cdot (\gamma^p - c) \cdot 1_{c \geq \gamma^p} + \mu^p + \epsilon_{apc} \quad (2)$$

where $\tilde{\beta}^p = \beta_a^p - \beta_c^p$. And the location, γ^p , and size δ^p , of the trend break by cohort are identified.

I estimate the model separately for each year, by weighted least squares, following the methodology in Hansen (2000) ³ Algorithmically, this amounts to looping through different assumed values of the trend break location γ^p , and selecting the location with the lowest sum of squared, weighted residuals.

Following Hansen (2000) I invert the following likelihood ratio statistic to form 99 percent confidence intervals for γ^p :

$$LR(\gamma^p) = n \frac{S(\gamma^p) - S(\hat{\gamma}^p)}{S(\hat{\gamma}^p)} \quad (3)$$

where n denotes the number of observations, $S(\gamma^p)$ is the weighted sum of squared residuals from estimating equation 3 with the trend break location fixed at a given γ^p , and $S(\hat{\gamma}^p)$ is the sum of squared residuals with the *estimated* break location $\hat{\gamma}^p$. I construct the 99 percent confidence interval as those values of γ^p such that $LR(\gamma^p) \leq 10.35$, the critical value given in Hansen (2000). While I allow for heteroskedasticity in inference on other parameters, this test requires homoskedasticity.

Hansen (2000) also suggests that inference on δ^p is unaffected by treating γ^p as unknown. I therefore form confidence intervals for δ^p using the standard formula for weighted least squares.

³As weights I use a consistent estimate of the inverse of the variance of observed log mortality in each cell: $\frac{\text{population} \cdot \text{mortality}}{(1 - \text{mortality})}$ (Schulhofer-Wohl and Yang, 2016).

Following standard practice, I employ an ad-hoc restriction to not allow the location of the cohort-break γ^p to be estimated to be one of the youngest or oldest cohorts in the sample — in particular, in each year I restrict the location of the break to not be one of the 3 youngest or oldest cohorts.

3.2 Graphical examples for select years

In this section, I present graphical evidence of a break in the cross-cohort mortality trend for a set of select years between 1985 and 2015.

I provide graphical examples of this trend-break estimation method for select years, based on fitting a piecewise linear model to log mortality rates of white men and women. I show plots including the true log mortality rate, and the piecewise linear model and the location of the trend break — estimated based on the procedure described above. Additionally, I show an extrapolation of the linear trend estimated for pre-break cohorts to younger cohorts, and plot the deviation of the true log mortality rates from the estimated pre-break linear trend. I restrict the sample to log mortality rates for 30-75 year old white men and women, born between 1930 and 1965.

Figure 1 implements this graphical example of the trend-break estimation method for the log mortality of white men in 1985, 1995, 2005, and 2015. The red circles show the true observed log mortality rate for each single year of age. The solid blue line shows the estimated trend-break model based on equation 2. The vertical, labeled gray line shows the cohort at which the trend break is estimated to occur for that year. The dotted blue line extrapolates the estimated linear trend for cohorts born before the trend break to younger, post-break cohorts.

Across the four year shown, the trend break is estimated to occur at different ages but at nearly the same cohort — suggesting it is the result of health differences across cohorts. The breaks by age are staggered with approximately 10 year gaps — occurring at ages 40, 48, 60, 68 for the years 1985, 1995, 2005, and 2015 respectively. As a result, the estimated breaks by cohort are nearly uniform — occurring at the 1944, 1946, 1944, and the 1946 cohort across the years shown.

Figure 2 plots the deviations of the true log mortality rates of white men from the estimated linear trend for pre-break cohorts. That is, it shows the difference between the pre-break trend — shown with a solid blue line for pre-break cohorts and a dotted blue line

for post-break cohorts in Figure 1 — and the true log mortality rates — shown in red circles. A horizontal gray line is now plotted at the 1946 cohort.

In each year shown, the deviations are near zero for cohorts born before 1946, implying that the a linear trend fits the log mortality rates well for these cohorts. Then suddenly at or near the 1946 cohort there is a trend break and the deviations increase for each subsequent cohort. The trend break is particularly large in 1985 and 1995, with the 1955 cohort for example experiencing log mortality rates approximately 60 and 40 log points, in the respective years, above what the Gompertz curve for earlier cohorts would predict. The trend break is smaller but still clearly evident in 2005 and 2015 — with the 1955 cohort experiencing log mortality rates around 20 and 15 log points above the prior trend in these two years.

Figure 3 replicates for white women the trend break examples shown in Figure 1. The trend break in log mortality is less visible striking for women than for men — but still evident and detected by the Hansen trend break estimation to occur at a similar cohort across years. The breaks by age are again staggered with approximately 10 year gaps — occurring at ages 37, 44, 56, 65 for the years 1985, 1995, 2005, and 2015 respectively. As a result, the estimated breaks by cohort are again close to uniform — though later than for men — occurring at the 1947, 1950, 1948, and the 1949 cohort across the years shown.

Figure 4 plots the deviations of the true log mortality rates of white women from the estimated linear trend for pre-break cohorts. That is, it shows the difference between the pre-break trend — shown with a solid blue line for pre-break cohorts and a dotted blue line for post-break cohorts in Figure 1 — and the true log mortality rates — shown in red circles. A horizontal gray line is now plotted at the 1946 cohort.

In each year shown, the deviations are near zero for cohorts born before 1946, implying that the a linear trend fits the log mortality rates well for these cohorts. Then suddenly at or near the 1946 cohort there is a trend break and the deviations increase for each subsequent cohort. The trend break is particularly large in 1985 and 1995, with the 1955 cohort for example experiencing log mortality rates approximately 60 and 40 log points, in the respective years, above what the Gompertz curve for earlier cohorts would predict. The trend break is smaller but still clearly evident in 2005 and 2015 — with the 1955 cohort experiencing log mortality rates around 20 and 15 log points above the prior trend in these two years.

3.3 Estimates for all years

I now implement the above described approach to estimate trend breaks in log mortality rates for all the years between 1985 and 2015. In particular, I estimate equation 2 for white women and men separately for each year between 1985 and 2015 — restricting the sample to ages 30-75, and cohorts 1930 to 1965.

Panels A and B of Figure 3 show the results across years for the log mortality rate of white women. The left panel shows for each year of data the estimated location of the cohort specific trend break, $\hat{\gamma}^p$, as well as the 99 percent confidence intervals. For all years from 1985 to 2015, the estimated trend break is between 1948 and 1952, and the confidence interval includes 1949. The right panel shows for each year the size of the estimated trend break, $\hat{\delta}^p$. The size of the trend break in log mortality is initially near .04 and then declines to nearer .02 after 1990.

I also use the asymptotically valid bootstrap procedure suggested in Hansen (1999) to test the null hypothesis of no break, eg. $H_0 : \delta^p = 0$. For all years, the value of the F-type statistic for the true data is larger than that calculated in all of the 1000 bootstrap repetitions that I run — implying a P-value of less than .001 for the null of no break.

Panels C and D of Figure 3 show analogous results for the log mortality rate of white men. The location of the trend break is slightly less stable for men than for women. From 1985 to 2004, the estimated trend break is precisely estimated and consistently located between 1945 and 1946, and the confidence interval includes 1946.

After 2004, the location becomes less precisely estimated. Between 2004 and 2009 the point estimate drops to near 1940 and the confidence interval no longer includes 1946. For 2009 to 2015, the point estimate jumps to 1945 and the confidence interval again includes 1946.

The size of the trend break for log mortality is initially larger for men than for women, it is above .06 for the first 7 years examined. In later years however it falls to near .02, similar to that estimated for women.

For men, in all years the implied P-value from the bootstrap procedure is less than .003 for the null of no break.

Overall, the results in this section demonstrate that the patterns shown for select years in Figures 1 through 4 are not anomalous. In each year between 1985 and 2015 there exist

slope changes in the age-profile of log mortality, which occur at or near the 1946 cohort for men and the 1949 cohort for women. The location of these trend breaks are precisely estimated. Further, in all years statistical tests provide strong evidence in favor of rejecting the null hypothesis that no change in slope exists. As outlined in the introduction, these slope changes are consistent with a cross cohort decline in health, beginning for white men born after 1946 and white women born after 1949.

4 A single structural break model

The above analysis allowed the location of the trend break in log mortality to vary by year. The results appear to suggest that the trend break occurs in the same cohort across years. Therefore, in this section I estimate a single structural break model across years, which imposes that the cohort-specific break occurs at the same cohort in all years. Guided by the above results, I allow the size of the break to vary across years. Estimation of this single model allows me to probe the robustness of the trend break results by including different specifications of a control function — which allows a separate polynomial in age for each year.

I again use the approach of Hansen (2000) to estimate the following model:

$$\ln(mort_{apc}) = \delta_{1,c}^p \cdot c + \delta_{2,c}^p \cdot 1_{c \geq \gamma} \cdot (c - \gamma) + f(a, p) + \epsilon_{apc} \quad (4)$$

where $\ln(mort_{apc})$ denotes the log mortality rate of the cell of age a , period p , and cohort c — for either white men or women. $\delta_{2,c}^p$ estimates the size of the break in each year p , and γ estimates the cohort at which a break occurs. I include increasingly flexible specifications of the “control function” $f(a, p)$. In most specifications the cohort trend $\delta_{1,c}$ is not separately identified from aspects of the control function, but main objects of interest, the size and location of the trend break are identified.

As above all models are estimated by weighted least squares, following the approach outlined in Hansen (2000). The sample includes the years 1985-2015, ages 30-75, and cohorts born from 1930-1970.

Table 1 reports the results of estimating equation 4, with the log mortality rate of white women or men for single age-by-year bins as the dependent variable. Each column contains the results from a separate regression, with progressively more flexible specifications of the

control function $f(a, p)$ from left to right.

Column 1 shows results from a model including a full-set of year fixed-effects, and a full set of age fixed-effects. This model is very flexible with respect to the shape of the age-profile in all years, but does not allow this shape to vary by year. All remaining columns include a full-set of year FEs, as well as progressively higher-order polynomials in age *interacted with year*. At the most extreme, column 4 allows a separate cubic in age for each year, so allows the impact of age on mortality to vary by year, albeit in a smooth parametric way.

The results for white women are shown in Panel A. For women the location of the trend break is consistently estimated to occur between the 1948 and 1950 cohort across all specifications. Additionally, the 99 percent confidence intervals, calculating by inverting the likelihood ratio statistic of Hansen (2000) are very tight, each including at most two cohorts.

For women the average size of the estimated cohort break — the average value of $\delta_{2,c}$ across all years—changes depending on the specification of the control function. It ranges from .040, with a standard error of .001, in the model with age and year fixed-effects, to .020, with the same standard error, when I allow for separate linear-age-by-year controls. Even the smallest estimate of .020, suggests a substantial impact on mortality. It implies that the white women born in 1948 have had on average a 22 percent higher mortality rate than if their mortality experience matched the trend for pre-1949 cohorts.

For each model I follow the bootstrap procedure described in Hansen (2000) to test the null hypothesis that no trend break occurs, ie. that $\delta_{2,c}^p$ is equal to 0 for all p . For all models, the value of the F-type statistic for the true data is larger than all of the 1000 bootstrap repetitions — suggesting a P-value of less than .001 for the null of no break.

Panel B reports analogous results with the log mortality rate of white men as the dependent variable. For white men, the estimated location of the trend break is even more consistent and precisely estimated. It is estimated to occur at the 1946 cohort across all specifications, and the 99 percent confidence intervals do not overlap any other cohorts.

As for women, the average size of the estimated cohort break for white men varies depending on the specification of the control function. The range of estimates are similar though slightly larger to that for women: ranging from .039, with a standard error of .001, in the model with age and year fixed-effects, to .025, with the same standard error, when I allow for cubic-age-by-year controls.

Again the even the smallest estimate of .025, suggests a non-trivial impact of the trend

break on mortality rates. It implies that the white men born in 1956 have had on average a 28 percent higher mortality rate than if their mortality experience matched the trend for pre-1946 cohorts.

For men as well, in all models the value of the F-type statistic for the true data is larger than all of the 1000 bootstrap repetitions — implying a P-value of less than .001 for the null of no break.

5 The cohort-specific trend break in log-mortality and year-over-year trends in mortality at different ages

I next use the previously estimated model to assess whether the cohort-specific pattern can explain the timing of recent increases, and stagnating improvements, in mortality by age. As described above, the timing by year of mortality trend breaks has not been uniform across age: while the age-adjusted mortality rate of non-Hispanics white women aged 45-54 began to increase in 1999 (Case and Deaton, 2015; Gelman and Auerbach, 2016), that of those aged 35-44 began to increase earlier in 1991, while that of 55-64 year olds continued to decline until a sudden break in 2010. Below, I use the shared cohort-specific trend break model estimated in the previous section to assess whether this cohort pattern can explain the staggered timing of mortality increases by age-bin. Intuitively, the question is whether “unhealthy” post-1949 cohorts have driven mortality increases first at young ages and subsequently at older ages, as they move through the age distribution.

To do so, I use the estimation results from the shared trend break model based on equation 4 and described in the previous section. I use the specification including a full set of year fixed-effects and a separate linear age effect for each year, reported in column 2 of Table 1. I then use the estimated model to simulate mortality rates by year and age group. Specifically, for each age-year cell I predict log mortality, and then calculate predicted mortality as the natural exponential of predicted log mortality, for each single age-by-year pair. Finally, I calculate the simulated age-adjusted mortality for age-bins as the simple average across single ages.

Figure 5 shows the true age-adjusted mortality rates and those simulated from the above model, for white women by year, for 35-44, 45-54, 55-64, year olds respectively. The simulated series closely tracks the true mortality rates for all age bins. Notably, the simulated mortality

rates match realized trend breaks in the mortality rate of 45-54 year olds in 1998 and of 55-64 year olds in 2010. The simulated series also nearly matches the increase in mortality of 35-44 year olds, predicting an increase starting after 1992 rather than the observed break in 1991.

Figure 6 shows analogous results for white men. The mortality experience of white men aged 35-44 shows the clear imprint of the AIDS epidemic — increasing between the early 1980s and 1995 and then declining sharply. Never the less, the simulated series from the simple cohort-specific trend break model again closely tracks the true mortality rates for all age bins. Again for men, the simulated mortality rates matches the observed trend break in the mortality rate of 45-54 year olds in 1998. It also matches the timing of the break for 55-64 year olds in 2010 — though the size of the true increase is larger than the simulated one.

There is a relatively tight mapping between the mortality rates predicted from the cohort-specific trend break model — without any other non-linear age-by-year interactions — and the true year-over-year patterns in mortality by age. This suggests that cohort specific differences in health plausibly played a key role in recent increases in mortality by age.

6 Lack of geographic variation

I show that the cohort-specific trend break in log mortality rates documented above is remarkably widespread across the United States, suggesting that the associated health decline is similarly widespread. To do so, I estimate the shared cohort-specific trend-break model of Section 4 separately for different states and regions of the United States.

First, I examine the location and size of the trend break by Census region. For each of the four regions, I estimate the trend break model based on equation 2 with a full set of year fixed-effects and a separate linear age effect for each year (similar national results are in column 2 of Table 1). I again follow Hansen (2000) and the procedure described above.

Panel A of Table 2 shows the results for white women. The precise cohort at which the trend break is estimated to have occurred varies only slightly across the four Census regions — from 1946 in the West to 1950 in the Midwest, with the estimates in the South and Northeast in between at 1948 and 1949 respectively. The average size of the estimated cohort break — the average value of $\delta_{2,c}$ across all years — ranges from a low of .018 in the West to a high of .024 in the Northeast. For all regions, the bootstrap procedure to test the

null hypothesis that no trend break occurs suggests a P-value of less than .001.

Panel B shows analogous results for white men. The cohort at which the trend break is estimated to have occurred again varies only slightly across the four Census regions — falling at 1942 in the West, 1946 in the Midwest and South, and 1944 in the Northeast. The average size of the estimated cohort break for men are *remarkably* similar across the four regions. This size is estimated to be identical up to 3 digits — at .026 — for the Northeast, South, and West. While the estimate for the Midwest is not far off at .029. For all regions, the bootstrap procedure to test the null hypothesis that no trend break occurs suggests a P-value of less than .001

To further explore potential geographic variation in the cohort-specific trend break I next examine it separately for each of the 50 states in the U.S. Given the smaller sample size at the state-level, I impose the *location* of the cohort-specific trend break in each state to match that at the national level. That is, I estimate separately for each state the trend break model based on equation 2 but fix γ_c to be 1949 for women and 1946 for men. I again use a specification with a full set of year fixed-effects and a separate linear age effect for each year, and estimate by weighted least squares — using the implied variance of log mortality as weights. For each state I then calculate the average size of the estimated cohort break — the average value of $\delta_{2,c}$.

Figure 7 shows maps and histograms of the distribution of these estimated break sizes for the 50 states — and demonstrates a surprising lack of variation in the size of the estimated breaks across states. No obvious regional patterns are apparent in the maps for either sex — the trend break is widespread across the United States. Further, *all 50 states* have estimated trend breaks which are positive in magnitude and greater than .01 for women and men. Estimates for women in all states are between .005 and .045, and 30 out of 50 states have estimated break sizes between .015 and .025. For men estimates range from .01 to .055, and 32 out of 50 states have break sizes between .025 and .035.

Appendix Figure 1 shows a scatter plot between the break sizes of men and women, and reveals a positive association. States with large breaks for men tend to also have large breaks for women. Alaska and Vermont stand out as states with large breaks for both men and women. On the other extreme, California and Florida have particularly small estimated breaks for both sexes. This positive association suggests that a single factor varying at the state-level may be driving health differences for both men and women. A regression of mens break sizes on womens break sizes confirms the positive relationship shown in the scatter

plot. Using the estimated variance of the female break sizes from the first-step as weights I perform a second-step, state-level regression. The estimated coefficient on male break size is .659, with a standard error of .079 and a corresponding t-statistic of 8.29.

7 Comparison to other ethnic groups

I next show some suggestive evidence that a similar — though smaller in magnitude — cohort-specific trend break in log morality rates to that for white Americans is evident for black women, and women and men of other races, but not for black men. I further show that the trend break documented above is concentrated among non-Hispanic whites — in years when it's possible to distinguish — and a similar break is not evident for Hispanics.

To do so, I estimate the shared cohort-specific trend-break model of Section 4 for other racial and ethnic groups. As in the previous section examining geographic heterogeneity, I estimate the trend break model based on equation 2 with a full set of year fixed-effects and a separate linear age effect for each year (as shown for all whites in column 2 of 1). I again follow Hansen (2000) and the procedure described above.

I first estimate the same model for blacks and Americans of all other racial groups combined. The sample again includes the years 1985-2015 and ages 30-75. I however restrict the cohorts included in the sample to 1930 to 1960. I do so to avoid inclusion of cohorts born near the passage of the Civil Rights Act — because previous research has suggested large improvements in health for blacks born after this period, due to increased hospital access following desegregation (Almond et al., 2006; Chay et al., 2009, 2014). Because of this sample restriction, I re-estimate the model for whites as well.

Results for women are shown in Panel A of Table 3. The cohort at which the trend break is estimated to occur is very similar across the 3 racial groups: 1949 for whites, 1946 for blacks, and 1948 for other races. The average size of the estimated trend breaks is positive for women of all racial groups, but the magnitude differs: from .0306 for white women, to .0199 for women of other races, and .0115 for black women.

Results for men are shown in Panel B — and those for black men differ substantially from the pattern for other groups. The cohort at which the trend break is again very similar for whites and the other racial group category: 1946 for white men, and 1944 for men of other races (with a confidence interval which includes 1946). And again the average size of

the estimated trend breaks are positive for both these groups: .0388 for white men and .0262 for men of other racial groups. However, for black men the location of the estimated trend break is the 1952 cohort and the average size is estimated to be slightly *negative* at -.0066.

A thorough analysis of trends in mortality and health for other racial groups — and an understanding of why they appear to differ for black men — is worthy of further study, but outside the scope of this paper. Two additional facts suggest that the differing pattern for black men may be linked in some way to the HIV epidemic. First, the mortality rate of HIV for black men — which was much higher than that for other racial groups — peaked for the 1952 cohort and declined for subsequent cohorts. Second, the cohort-specific decline in log mortality rates after the 1952 cohort, relative to the preceding trend, appeared suddenly in the late 90s.⁴

I then estimate the above model for the years after 1997 — when Hispanic-origin is reported on death certificates in all states — separately for i) all whites, regardless of Hispanic-origin; ii) non-Hispanic whites; and iii) Hispanic whites. The sample includes the years 1997-2014, cohorts born 1930 to 1970, and ages 30 to 75. Results are shown in Appendix Table 1.

Overall, the results show that — in this period — restricting estimation to non-Hispanic whites alone increases the size of the estimated cohort-specific trend breaks, suggesting the health decline may be concentrated among non-Hispanic whites. Panel A of Appendix Table 1 shows results for white women. When the model is estimated on the full population of white women, regardless of Hispanic origin the estimated average size of break is .0145. When the population is restricted to non-Hispanic white women the estimate break size grows to .0229. The estimated cohort at which the trend break occurs also shifts slightly from 1948 to 1950, for all whites and non-Hispanic whites respectively.

Similar results can be seen for men in Panel B. The estimated average size of break increase from .0106 for all white men, to .0164 for non-Hispanic whites. The estimated cohort at which the trend break occurs is 1946 for both groups.

In contrast, the estimated location of the trend break for Hispanic white women and men is 1939. The estimated size of breaks are positive and of a similar magnitude to that for non-Hispanic whites: .0194 and .0149 for women and men respectively. The apparently different cohort-specific pattern of health for Hispanics is outside the scope of this study —

⁴Results available from author by request.

but could be potentially due to changing immigration patterns.

Overall, the above results suggest that the cohort-specific trend break in log mortality rates — and implied decline in health — documented in the rest of the paper was concentrated among non-Hispanic whites; and a similar pattern appears to exist for black women, men and women of other races, but not for black men or Hispanic men or women. The trend breaks for other racial groups that do exist are smaller than those observed for whites.

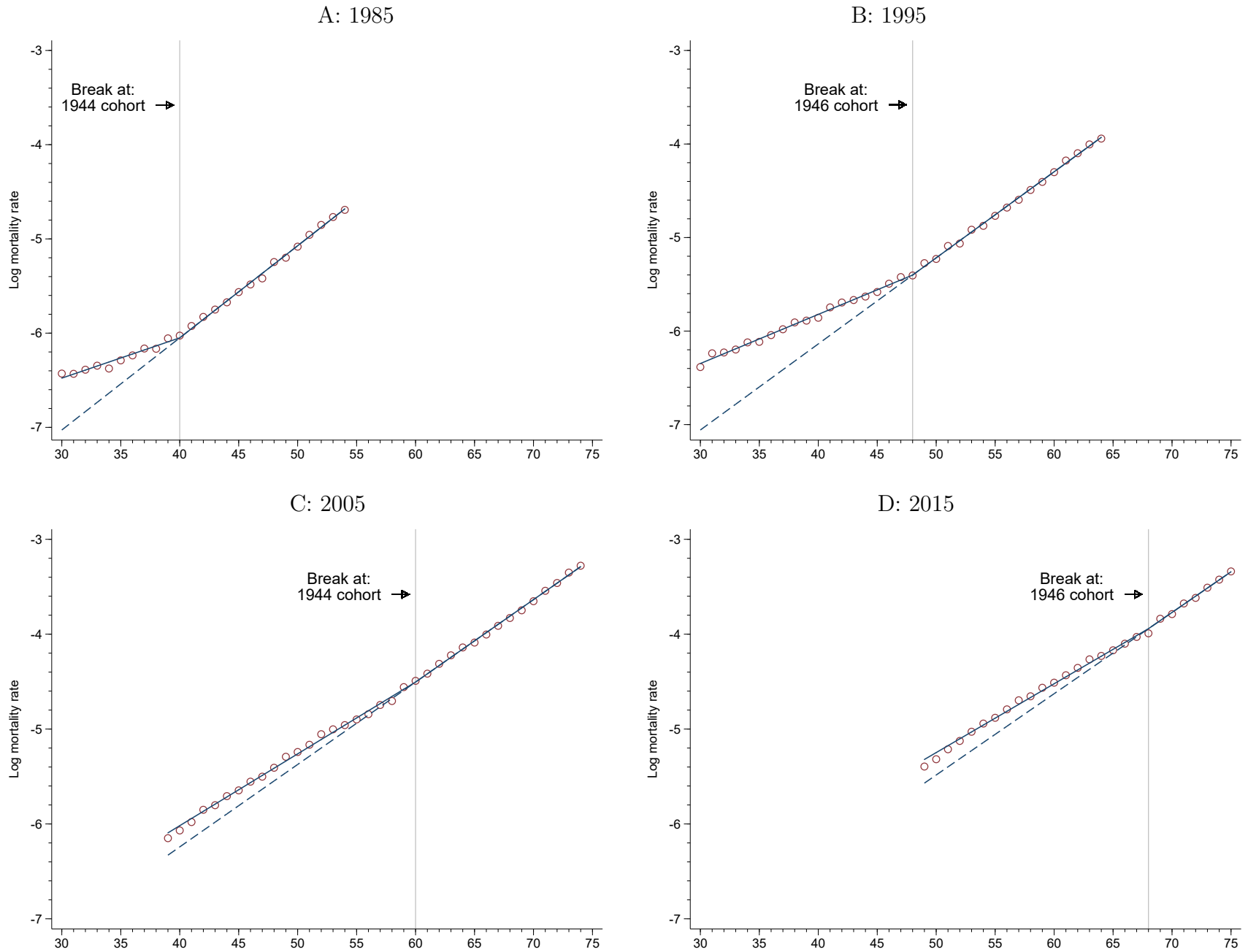
8 Conclusion

In this paper I document a sharp pattern in white mortality rates which suggests that the health of white women born since 1949 and white men born since 1946 suddenly declined relative to the trend for preceding cohorts. The uncovering of this apparent cross-cohort health decline could motivate further research in two directions: one trying to uncover the root cause of the decline; and two, exploring its implications beyond mortality.

That increased mortality of white Americans appears cohort-specific suggests it's causes are as well: differing early life circumstances, or long-standing differences in health behaviors or labor market outcomes; rather than recent changes. Future research should consider specific theories of the cause of this cohort-specific health decline and test their predictions. The precise timing of the cohort-specific health decline which I've documented can substantially aid and provide discipline in this search: any theory of the cohort health decline must be able to explain why it began with the 1946 cohort for men and the 1949 cohort for women.

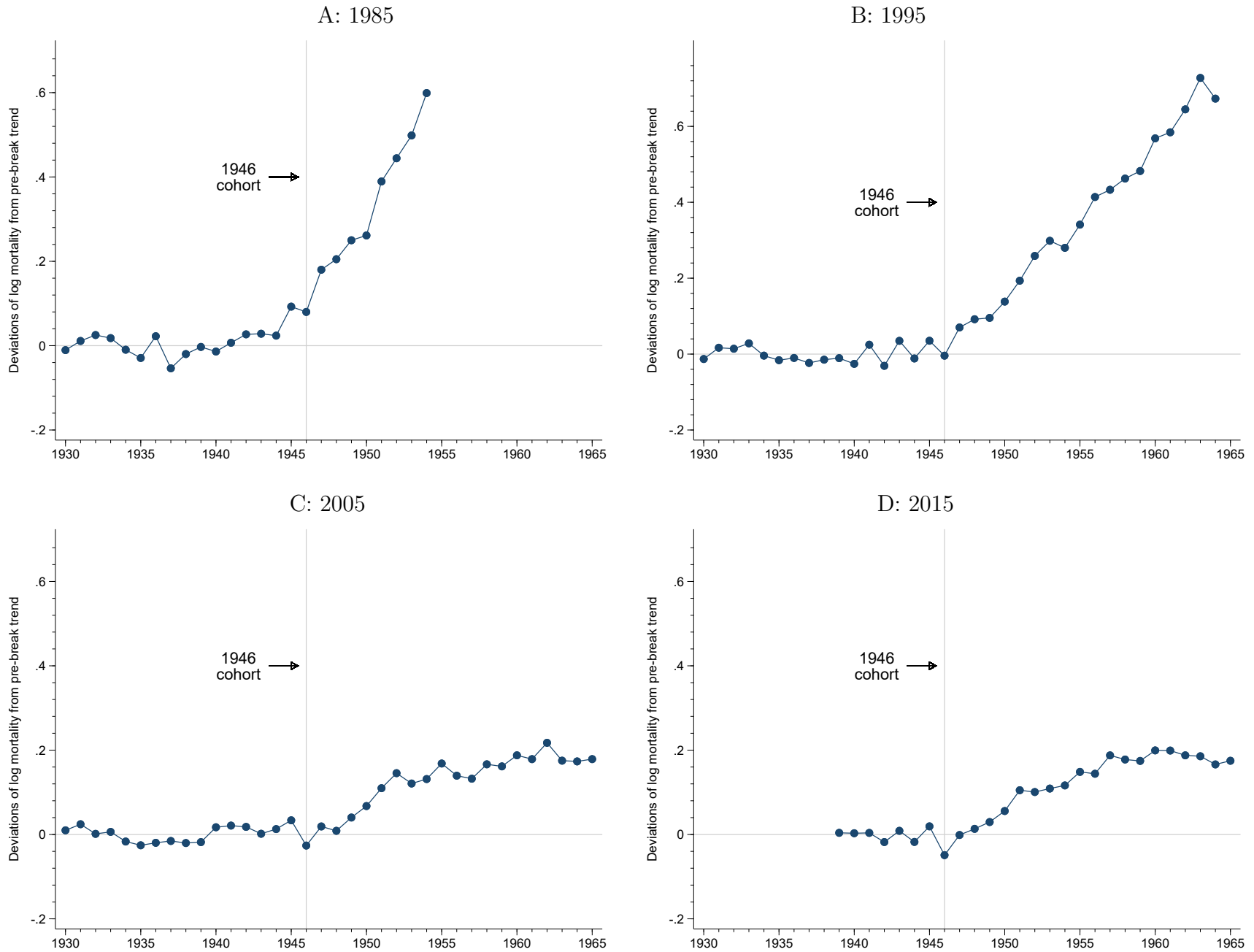
Further, a decline in the health of cohorts born since the late-1940s should have many implications distinct from it's impact on mortality rates. The apparently unhealthy cohorts are about to enter old age and their depressed health could increase health care spending, depress labor force participation, and impact the solvency of programs such as Medicare.

Figure 1: Trend break in log mortality rates, white men — select years



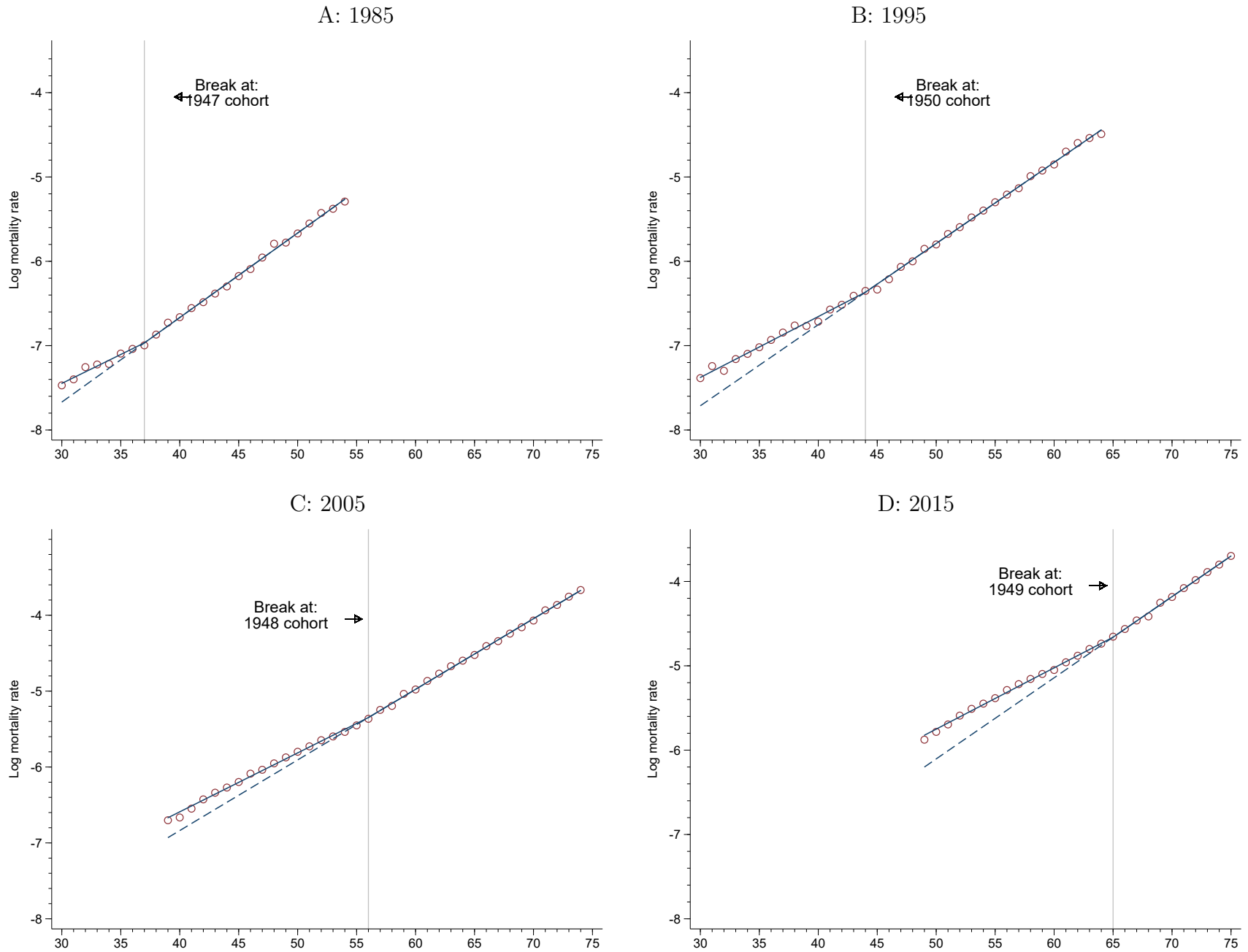
Each plot shows the log mortality rate of white men by age for the year listed, for 1930 to 1965 cohorts. Red circles show the observed log mortality rate by single year of age. The solid blue line shows plots the piecewise-linear, trend-break model estimated by weighted-least squares based on equation 2. The vertical gray line shows the age/cohort of the estimated break in trend. The dotted blue line extrapolates the linear trend for cohorts born before the break to post-break cohorts.

Figure 2: Deviations of log mortality from trend for pre-break cohorts, white men — select years



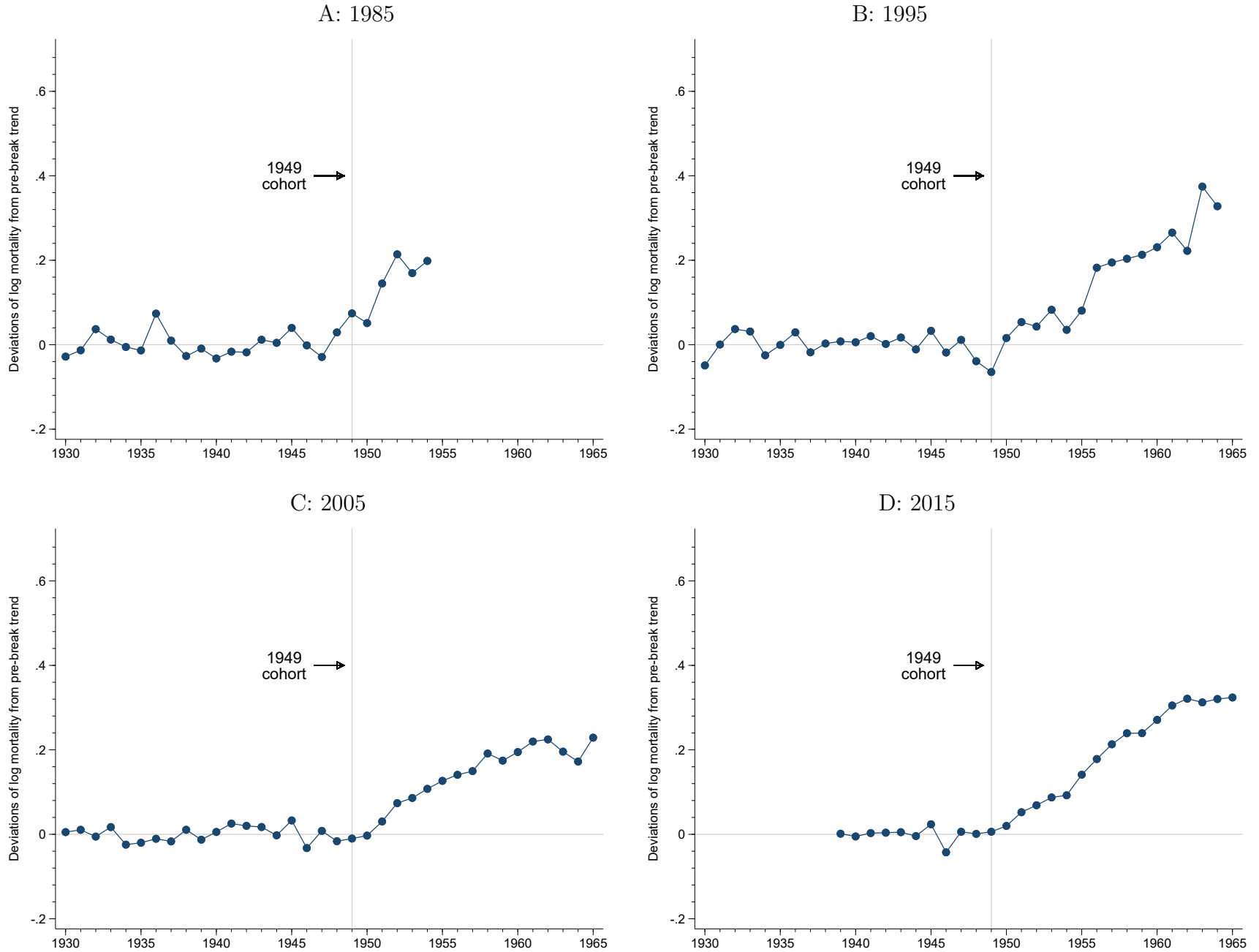
Each plot shows the deviations of the true log mortality rates of white men from the estimated linear trend for cohorts born before an estimated trend break for the year listed. The initial piecewise-linear, trend-break model is estimated by weighted-least squares based on equation 2, following the approach outlined in Hansen (2000). A horizontal gray line is plotted at the 1946 cohort. Sample is restricted to men born between 1930 and 1965.

Figure 3: Trend break in log mortality rates, white women — select years



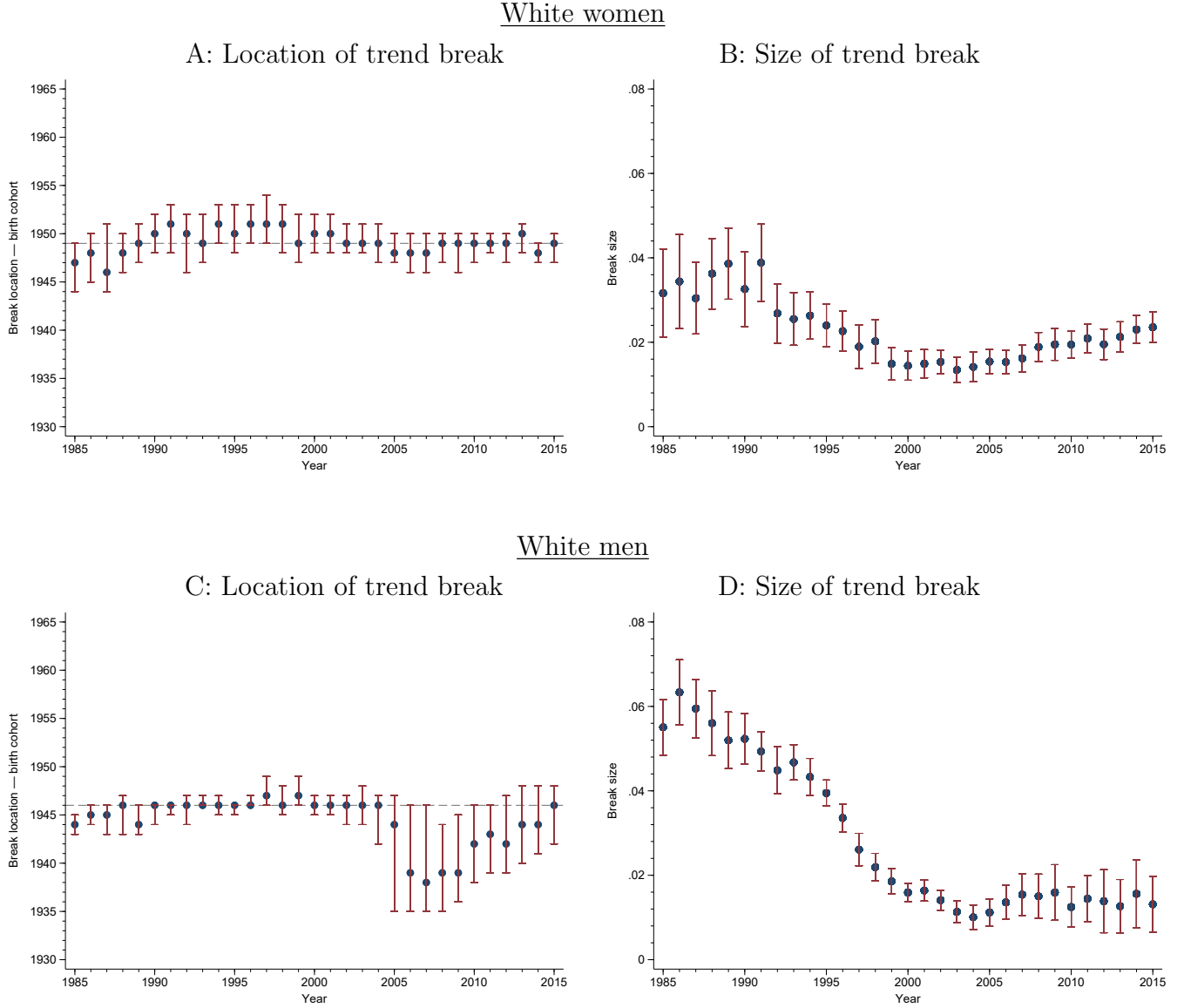
Each plot shows the log mortality rate of white women by age for the year listed, for 1930 to 1965 cohorts. Red circles show the observed log mortality rate by single year of age. The solid blue line shows plots the piecewise-linear, trend-break model estimated by weighted-least squares based on equation 2. The vertical gray line shows the age/cohort of the estimated break in trend. The dotted blue line extrapolates the linear trend for cohorts born before the break to post-break cohorts.

Figure 4: Deviations of log mortality from trend for pre-break cohorts, white women — select years



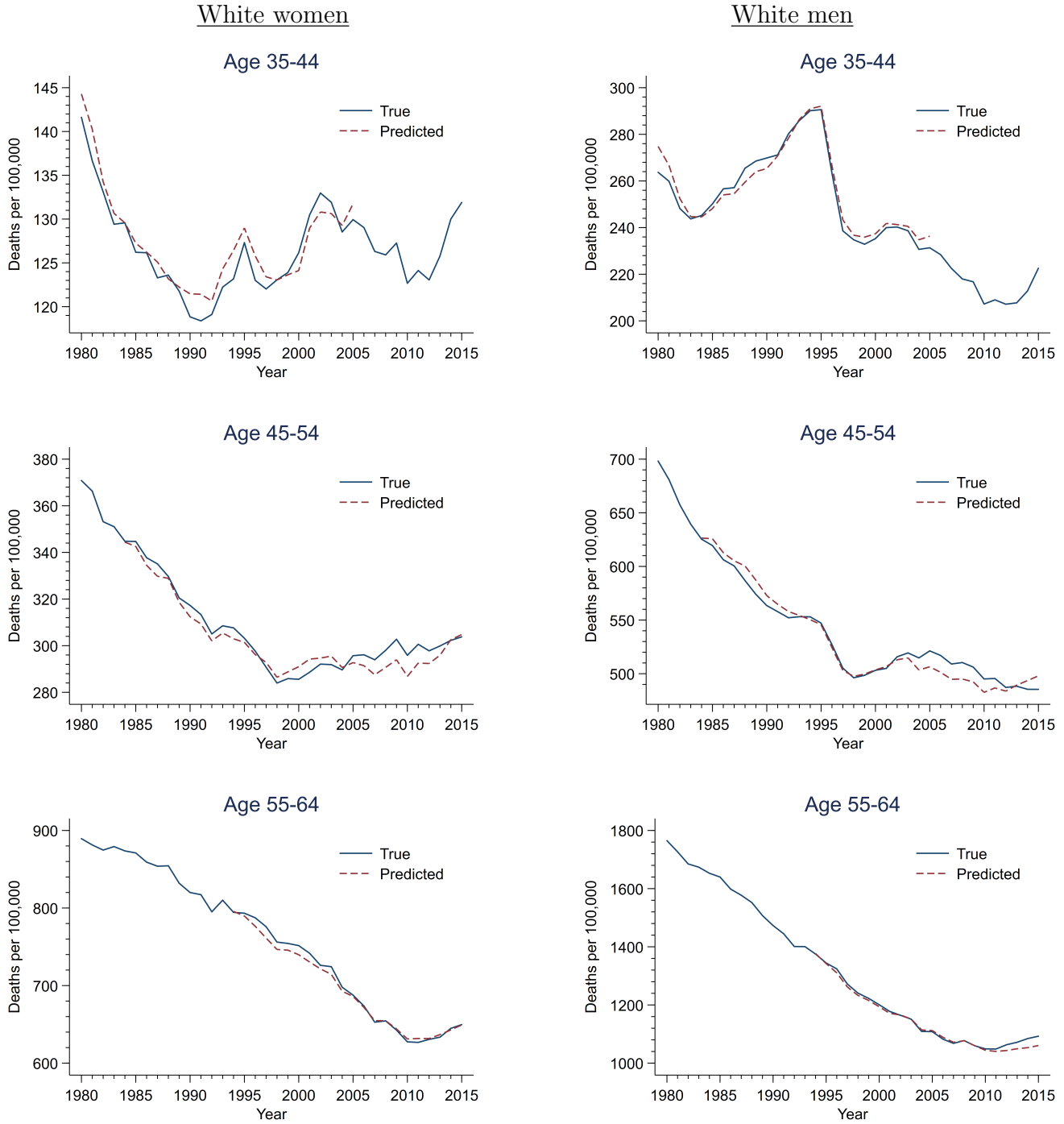
Each plot shows the deviations of the true log mortality rates of white women from the estimated linear trend for cohorts born before an estimated trend break for the year listed. The initial piecewise-linear, trend-break model is estimated by weighted-least squares based on equation 2. A horizontal gray line is plotted at the 1946 cohort. Sample is restricted to men born between 1930 and 1965.

Figure 5: Log mortality trend break and size estimates, separately by year



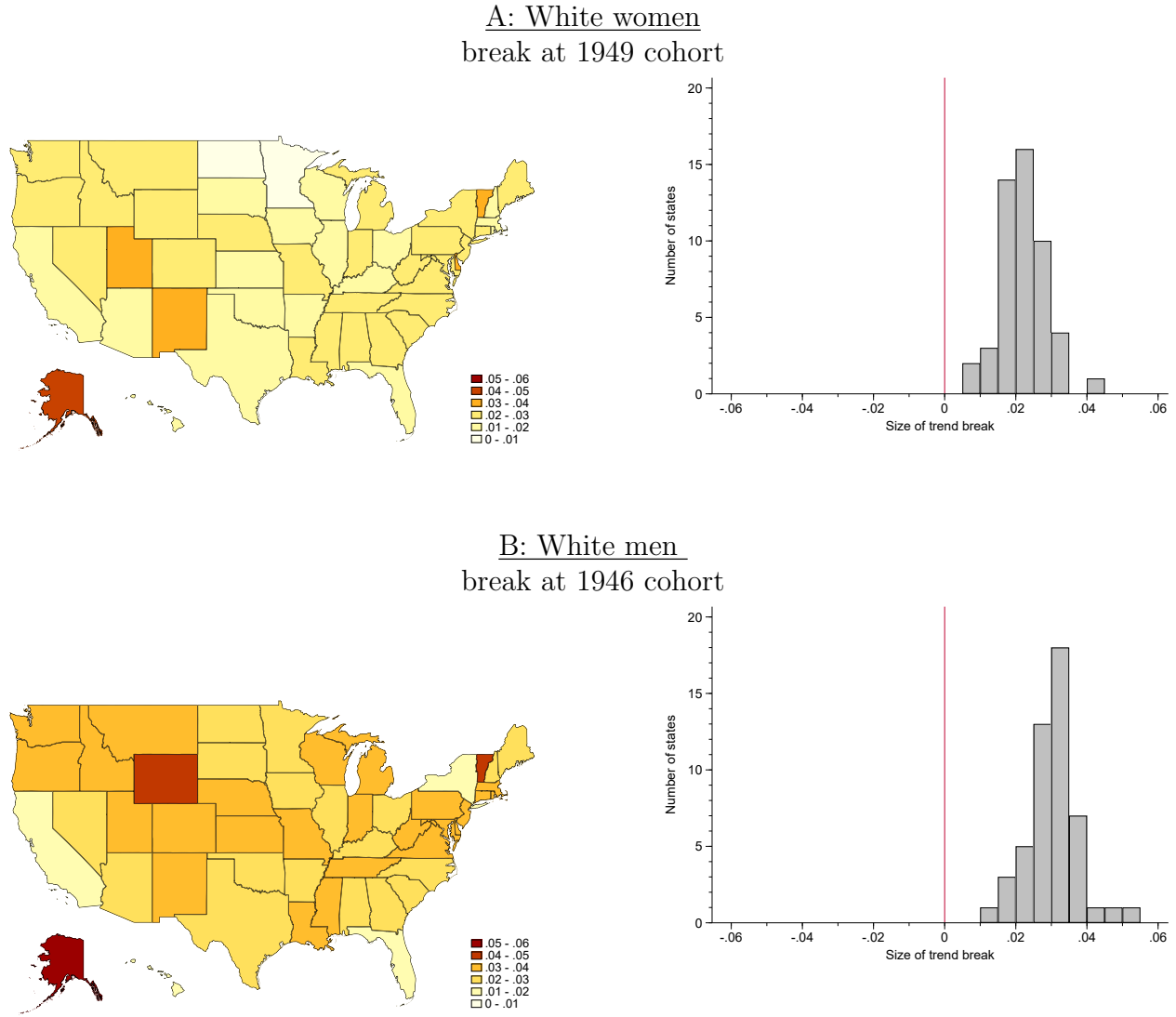
These figures show the results of estimation of the trend break model in equation 6, with the log mortality rate of white women or men by age, year and cohort as the dependent variable. A separate model is estimated for each year by weighted least squares, following the approach outlined in Hansen (2000). The sample includes ages 30-75, and cohorts 1930 to 1965. The left panel shows for each year of data the estimated location of the cohort specific trend break, $\hat{\gamma}^p$, as well as the 99 percent confidence interval calculated by inverting a likelihood ratio test statistic. The right panel shows for each year the size of the estimated trend break, $\hat{\delta}^p$.

Figure 6: True mortality rates and those predicted by a model with cohort-specific trend break



Each plot shows the true age-adjusted mortality rates and those predicted from a model including a cohort-specific trend break, for white women or men by year, for 35-44, 45-54, 55-64, year olds respectively. The true age-adjusted mortality rates are the simple average across single ages — ie. age adjusted assuming a uniform population distribution by age. To form the predicted series, I use the estimation results from a shared trend break model based on equation 5. I use the specification including a full set of year fixed-effects and a separate linear age effect for each year, reported in column 2 of Table 1. For each age-year cell I predict log mortality using this model, and then calculate predicted mortality as the natural exponential of predicted log mortality, for each single age-by-year pair. Finally, I calculate the simulated age-adjusted mortality for age-bins as the simple average across single ages.

Figure 7: Little variation across states in size of cohort-specific trend break in log mortality



This figure shows the variation across states in the size of cohort-specific trend breaks in the log mortality of white women and men. All figures are based on separate estimation by state of cohort-specific trend break models of the log mortality of white women or men. Each model is based on equation 4 including a full set of year fixed-effects and a separate linear age effect for each year. The location of the trend break γ is treated as known — 1946 for men and 1949 for women — and estimation is done by weighted least squares. The sample includes the years 1985-2015, ages 30-75, and cohorts born from 1930-1970. For each state I calculate the average value of the trend break $\delta_{2,c}$ across all years. The maps display the values of these average trend break sizes for each state. The histograms show the distribution of these average trend break sizes across the 50 states.

Table 1: Shared cohort-specific trend break, log mortality of white Americans 1980-2015

	(1)	(2)	(3)	(4)
<u>Panel A: White women</u>				
Average size of break	0.040 (0.001)	0.020 (0.001)	0.034 (0.001)	0.024 (0.002)
Location of break	1949 [1949, 1949]	1948 [1948, 1949]	1949 [1949, 1949]	1950 [1950, 1950]
P-value for existence of break	< .001	< .001	< .001	< .001
<u>Panel B: White men</u>				
Average size of break	0.039 (0.001)	0.026 (0.001)	0.029 (0.001)	0.025 (0.002)
Location of break	1946 [1946, 1946]	1946 [1946, 1946]	1946 [1946, 1946]	1946 [1946, 1946]
P-value for existence of break	< .001	< .001	< .001	< .001
Year FEs	Yes	Yes	Yes	Yes
Age FEs	Yes	No	No	No
Linear-age-by-year	No	Yes	Yes	Yes
Quadratic-age-by-year	No	No	Yes	Yes
Cubic-age-by-year	No	No	No	Yes

Each column shows the results of estimation of a model based on equation 4, with the log mortality rate of white men or women for single age-by-year bins as the dependent variable. All models are estimated by weighted least squares, following the approach outlined in Hansen (2000). The sample includes the years 1980-2015, ages 30-75, and cohorts born from 1930-1970. The row titled “Average size of break” reports the average value of $\delta_{2,c}$ across all years, with the standard error in parentheses calculated by the delta method. The row titled “Location of break” reports the estimated cohort at which a trend break occurs, with a 99 % confidence interval in brackets calculated by inverting the likelihood ratio statistic. The row titled “P-value for existence of break” reports p-value from an F-type test for the null hypothesis that no trend break occurs, based on 1000 bootstrap samples.

**Table 2: Shared cohort-specific trend break, log mortality of white Americans
By Census Region, 1980-2014**

	(1) Northeast	(2) Midwest	(3) South	(4) West
<u>Panel A: White women</u>				
Average size of break	0.024 (0.001)	0.021 (0.001)	0.020 (0.001)	0.018 (0.001)
Location of break	1949 [1949, 1949]	1950 [1950, 1950]	1948 [1947, 1948]	1946 [1946, 1946]
P-value for existence of break	< .001	< .001	< .001	< .001
<u>Panel B: White men</u>				
Average size of break	0.026 (0.001)	0.029 (0.001)	0.026 (0.001)	0.026 (0.001)
Location of break	1944 [1944, 1944]	1946 [1946, 1946]	1946 [1946, 1947]	1942 [1942, 1943]
P-value for existence of break	< .001	< .001	< .001	< .001
Linear age	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Linear-age-by-year	Yes	Yes	Yes	Yes
Quadratic-age-by-year	No	No	No	No
Cubic-age-by-year	No	No	No	No

Each column shows the results of estimation of a model based on equation 4, with the log mortality rate of white men or women — in the listed Census Region — for single age-by-year bins as the dependent variable. All models are estimated by weighted least squares, following the approach outlined in Hansen (2000). The sample includes the years 1980-2014, ages 30-75, and cohorts born from 1930-1970. The row titled “Average size of break” reports the average value of $\delta_{2,c}$ across all years, with the standard error in parentheses calculated by the delta method. The row titled “Location of break” reports the estimated cohort at which a trend break occurs, with a 99 % confidence interval in brackets calculated by inverting the likelihood ratio statistic. The row titled “P-value for existence of break” reports p-value from an F-type test for the null hypothesis that no trend break occurs, based on 1000 bootstrap samples.

**Table 3: Shared cohort-specific trend break, log mortality
By Race, 1980-2015
Cohorts born 1960 and earlier**

	(1) Whites	(2) Blacks	(3) Other races
<u>Panel A: Women</u>			
Average size of break	0.0306 (0.0022)	0.0115 (0.0013)	0.0199 (0.0066)
Location of break	1949 [1949, 1950]	1946 [1944, 1947]	1948 [1947, 1949]
P-value for existence of break	< .001	< .001	< .001
<u>Panel B: Men</u>			
Average size of break	0.0388 (0.0008)	-0.0066 (0.0029)	0.0262 (0.0017)
Location of break	1946 [1946, 1946]	1952 [1951, 1952]	1944 [1944, 1946]
P-value for existence of break	< .001	< .001	< .001
Linear age	Yes	Yes	Yes
Year FEs	No	No	No
Linear-age-by-year	Yes	Yes	Yes
Quadratic-age-by-year	No	No	No
Cubic-age-by-year	No	No	No

Each column shows the results of estimation of a model based on equation 4, with the log mortality rate of men or women, of the listed racial group, for single age-by-year bins as the dependent variable. All models are estimated by weighted least squares, following the approach outlined in Hansen (2000). The sample includes the years 1980-2014, ages 30-75, and cohorts born from 1930-1960. The row titled “Average size of break” reports the average value of $\delta_{2,c}$ across all years, with the standard error in parentheses calculated by the delta method. The row titled “Location of break” reports the estimated cohort at which a trend break occurs, with a 99 % confidence interval in brackets calculated by inverting the likelihood ratio statistic. The row titled “P-value for existence of break” reports p-value from an F-type test for the null hypothesis that no trend break occurs, based on 1000 bootstrap samples.

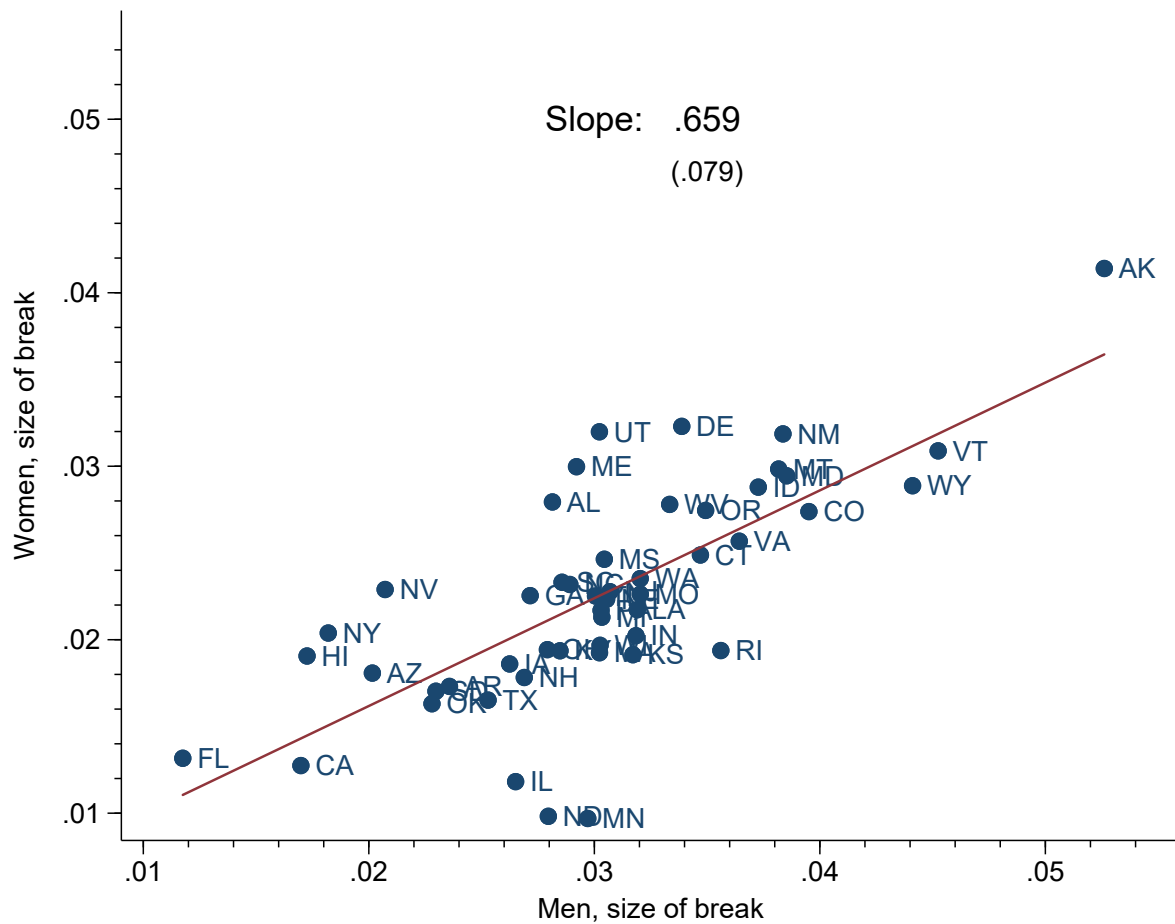
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Appendix Figure 1: Relationship between state-level size of cohort-specific trend break in white log mortality for women and men



This figure shows the relationship across the 50 states between the size of cohort-specific trend breaks in log mortality for white women and those for white men. The first step is separate estimation by state of cohort-specific trend break models of the log mortality of white women or men. Each model is based on equation 4 including a full set of year fixed-effects and a separate linear age effect for each year. The location of the trend break γ is treated as known — 1946 for men and 1949 for women — and estimation is done by weighted least squares. The sample includes the years 1985-2014, ages 30-75, and cohorts born from 1930-1970. For each state I calculate the average value of the trend break $\delta_{2,c}$ across all years. The above figure plots this average value for each state for men versus the average value for women in the same state. The second step is a regression with the estimated break sizes of women as the dependent variable and that of men as the independent variable. The variance of women’s estimated break size from the first step are used as weights in the second step.

Appendix Table 1: Shared cohort-specific trend break, log mortality of white Americans
By Hispanic origin, 1997-2014

	(1) All whites	(2) Non-Hispanic whites	(3) Hispanic whites
<u>Panel A: White women</u>			
Average size of break	0.0145 (0.0004)	0.0229 (0.0006)	0.0194 (0.0023)
Location of break	1948 [1948, 1948]	1950 [1950, 1950]	1939 [1939, 1939]
P-value for existence of break	< .001	< .001	< .001
<u>Panel B: White men</u>			
Average size of break	0.0106 (0.0005)	0.0164 (0.0005)	0.0149 (0.0024)
Location of break	1946 [1944, 1946]	1946 [1946, 1946]	1939 [1938, 1940]
P-value for existence of break	< .001	< .001	< .001
Linear age	Yes	Yes	Yes
Year FEs	No	No	No
Linear-age-by-year	Yes	Yes	Yes
Quadratic-age-by-year	No	No	No
Cubic-age-by-year	No	No	No

Each column shows the results of estimation of a model based on equation 4, with the log mortality rate for single age-by-year bins as the dependent variable. The columns respectively show results for the mortality rate of i) all whites, regardless of Hispanic origin; ii) non-Hispanic whites; and iii) Hispanic whites. All models are estimated by weighted least squares, following the approach outlined in Hansen (2000). The sample includes the years 1997-2014, ages 30-75, and cohorts born from 1930-1970. The row titled “Average size of break” reports the average value of $\delta_{2,c}$ across all years, with the standard error in parentheses calculated by the delta method. The row titled “Location of break” reports the estimated cohort at which a trend break occurs, with a 99 % confidence interval in brackets calculated by inverting the likelihood ratio statistic. The row titled “P-value for existence of break” reports p-value from an F-type test for the null hypothesis that no trend break occurs, based on 1000 bootstrap samples.