Journal of Economic Perspectives—Volume 35, Number 4—Fall 2021—Pages 123–146

Rising Geographic Disparities in US Mortality

Benjamin K. Couillard, Christopher L. Foote, Kavish Gandhi, Ellen Meara, and Jonathan Skinner

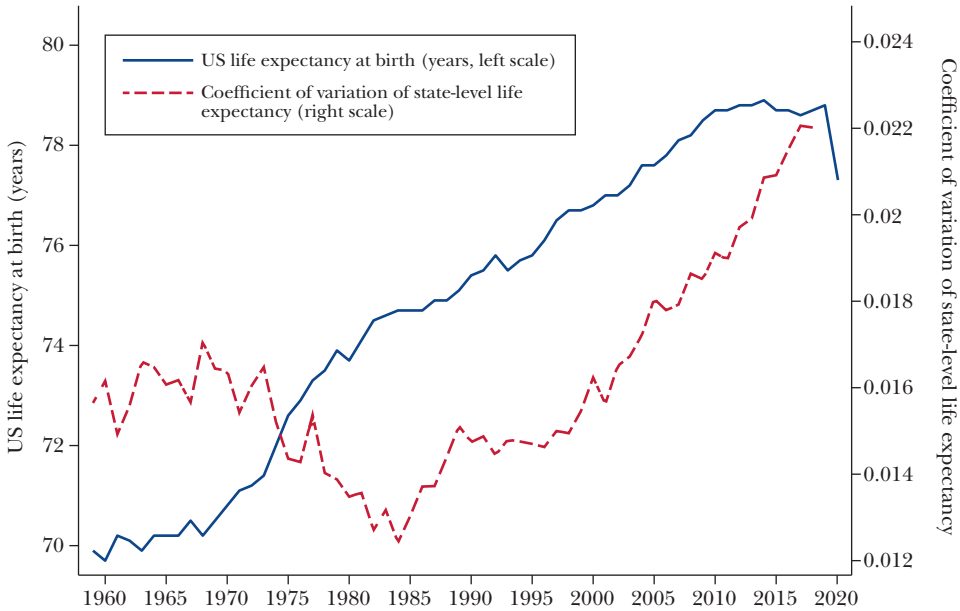
Until recently, Americans could expect to live longer than their parents. Overall US life expectancy rose steadily from the 1960s through the early 2000s. As Figure 1 shows, the 1.5-year drop in life expectancy in 2020 signaled a sharp reversal; indeed, it was the largest decline since World War II. But even before the Covid-19 pandemic, US life expectancy was essentially flat for about a decade and had even declined slightly after 2014. Public health officials and health researchers have become increasingly concerned about this plateau, and, as they studied it, another important fact has emerged: disparities in mortality have become increasingly apparent among different groups in the population.

Much of the recent research on life expectancy focuses on particularly worrisome mortality trends for persons at midlife, defined as ages 25–64. A recent report from the National Academy of Sciences, Engineering, and Medicine (2021) reviews this work and links high and rising midlife mortality rates to two main factors. First, rapid progress that had been made in reducing mortality from some major causes, most notably heart disease, stalled after 2010. Second, deaths from suicide, drug

■ *Benjamin K. Couillard is a PhD student in Economics, University of Toronto, Toronto, Canada. Christopher L. Foote is a Senior Economist and Policy Adviser, Federal Reserve Bank of Boston, Boston, Massachusetts. Kavish Gandhi is a Research Assistant, Federal Reserve Bank of Boston, Boston, Massachusetts. Ellen Meara is Professor of Health Economics and Policy, Harvard T.H. Chan School of Public Health, Boston, Massachusetts. Jonathan Skinner is a Research Professor in Economics, Dartmouth College, Hanover, New Hampshire. Meara and Skinner are also Research Associates, National Bureau of Economic Research, Cambridge, Massachusetts. Their email addresses are bcouillard22@gmail.com, chris.foote@bos.frb.org, kavish.gandhi@bos.frb.org, emeara@hsph.harvard.edu, and jon.skinner@dartmouth.edu.*

For supplementary materials such as appendices, datasets, and author disclosure statements, see the article page at https://doi.org/10.1257/jep.35.4.123.

Figure 1
US Life Expectancy at Birth and State-Level Dispersion in Income



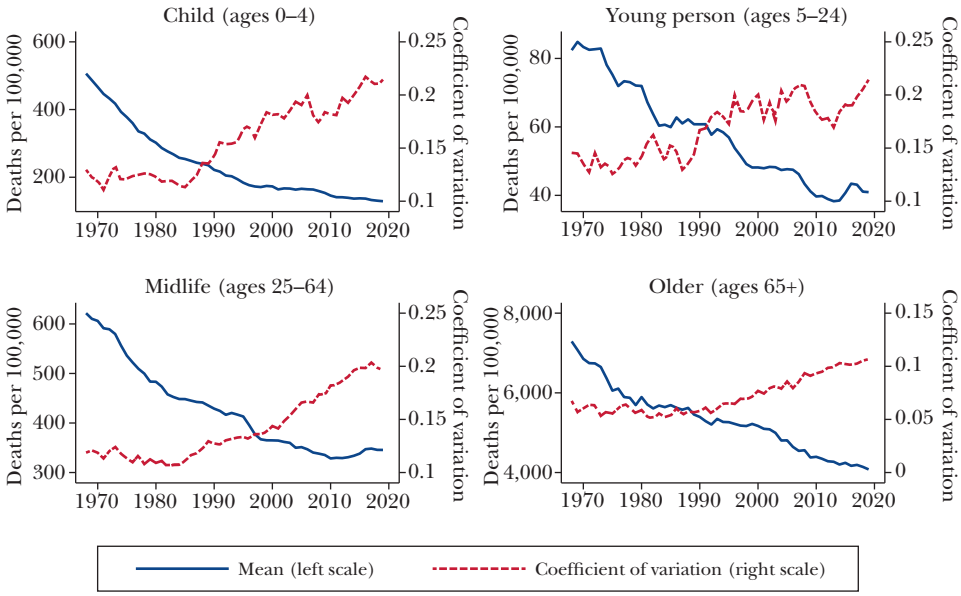
Source: The national life-expectancy rate (1959–2020) is from the National Center for Health Statistics, and state-level rates (1959–2018) are from the USA Mortality Database (https://usa.mortality.org).
Note: The coefficient of variation is the population-weighted standard deviation of state-level life-expectancy rates divided by the national life-expectancy rate.

poisoning, and alcohol-induced causes have risen sharply. These deaths, often labeled "deaths of despair," have been the focus of extensive research by Anne Case and Angus Deaton (2015, 2017, 2020). Regarding mortality disparities, the NAS report noted large and widening mortality differences based on race, ethnicity, economic status, and geography. For example, recent increases in mortality among Black and Hispanic persons have undone years of progress in addressing high mortality rates among these groups (Harris, Woolf, and Gaskin 2021).

In this paper, we document and analyze rising geographic disparities in health, focusing on the state level. Vierboom, Preston, and Hendi (2019) highlight growing local inequality in longevity after 2000; coastal cities gained while rural Appalachia and the South lagged behind. Among US states, Woolf and Schoomaker (2019) document divergence in life expectancy beginning about a decade earlier. Figure 1 shows that the coefficient of variation of state life-expectancy rates (defined as the standard deviation of these rates divided by the mean) began to rise long before average US life expectancy flattened out.

Figure 2 shows that dispersion in state-level life expectancy has been generated by increased dispersion in mortality throughout the age distribution. For the most part, average group-specific mortality rates have trended downward for each of the

Figure 2
Mortality Rates by Age Group (1968–2019)



Source: CDC Wonder database (https://wonder.cdc.gov/).
Note: Data are population-weighted statistics based on state-level age-adjusted mortality rates, defined as deaths per 100,000 persons. The coefficient of variation is the standard deviation of state-level mortality rates divided by the mean.

four age groups depicted (0–4, 5–24, 25–64, and 65+). The stalling of US life expectancy around 2010 resulted from a flattening out of mortality (or outright increases in mortality) for the three age groups younger than 65. But in each of the four groups, dispersion has generally trended higher during the last several decades, especially for the three youngest groups. Although recent trends in race-specific mortality rates contribute to geographic dispersion in mortality, racial patterns alone do not explain why mortality experiences have become more unequal at the state level. Indeed, state-level dispersion has been rising among Black and White non-Hispanic populations separately, while a declining dispersion trend for Hispanics has recently flattened out (as we show in the online Appendix available with this article at the *JEP* website).

What are the most important drivers of mortality divergence across states? One explanation is that geographic disparities are driven by differences in education levels and labor market prospects (Meara, Richards, and Cutler 2008; Case and Deaton 2015, 2017, 2020). In this view, states with relatively large or quickly growing college shares experienced large gains in life expectancy, because recent health gains have been concentrated among Americans with college degrees. As the mortality "penalty" associated with a non-college education grew over time, states with smaller college-educated populations lagged behind.

A second and possibly related explanation is that greater dispersion in state-level mortality rates has been driven by the rising spatial inequality in income. Income is unevenly distributed across the United States, and after converging for most of the 20th century, regions of the country are now growing apart economically (Ganong and Shoag 2017; Gaubert et al. 2021). Chetty et al. (2016) have documented a strong association between income and mortality in the United States. However, much less is known about the influence of longer-term swings over a quarter-century in growth rates of income or about how changing economic circumstances affect common causes of deaths, such as heart disease and cancer.

A third possibility is that the widening divergence in mortality stems from a portmanteau of "place" effects that are independent of state-level income. We think of these effects as capturing both the health behaviors of individuals who live in a place and the evolving features of the region's overall health environment. Much of the prior literature on regional economic conditions and mortality has focused on "deaths of despair," comparing changes in these deaths to economic shocks over relatively short periods of time (Autor, Dorn, and Hanson 2019; Pierce and Schott 2020; Charles, Hurst, and Schwartz 2018; Ruhm 2017; Hollingsworth, Ruhm, and Simon 2017; Ruhm 2019). In contrast to these short-run mechanisms, health disparities across states may arise from long-run changes in state policies or health "investments" that gradually enhance health and longevity (Montez and Berkman 2014; Montez et al. 2019). Examples of long-run health investments include anti-smoking policies, expansions of Medicaid, income support, and norms around health behaviors.

We use data on mortality, income, health behavior, and health-care quality to test these alternative hypotheses for the growth in state-level disparities. Like the recent NAS report and the work of Case and Deaton, we focus on mortality at midlife. We find that national trends in educational attainment and a rising national correlation between education and mortality ultimately explain little of the increasing importance of place in determining mortality. We do not find evidence that states with the most rapid income *growth* experienced the most rapid mortality decline. Instead, states with relatively high income *levels* over the past several decades have experienced the largest improvements in midlife mortality. Although deaths of despair have contributed to the plateau in US life expectancy, even after their recent growth they account for only about one-sixth of all midlife deaths, and we show that midlife disparities are driven largely by other causes of death. Finally, reviewing the growing literature on "place" and health, we argue that the most promising explanation for our findings involve efforts by high-income states to adopt specific health-improving policies and behaviors since at least the early 1990s. Over time, these efforts reduced mortality in high-income states more rapidly than in low-income states, leading to widening spatial disparities in health.

Education and the Rising Dispersion in State-Level Mortality Rates

In a series of important papers and a recent book, Case and Deaton (2015, 2017, 2020, 2021) have documented the striking differences in mortality rates for

Americans with different levels of education. In considering why the spatial dispersion of midlife mortality rose during the past two decades, we first consider the well-known divergence in mortality for people with and without college degrees. Because states differ in their college-educated population shares, the growing national difference between college and non-college mortality rates would by itself generate disparity in state-level mortality, particularly if college-educated persons tended to migrate to states where college attainment was already high.

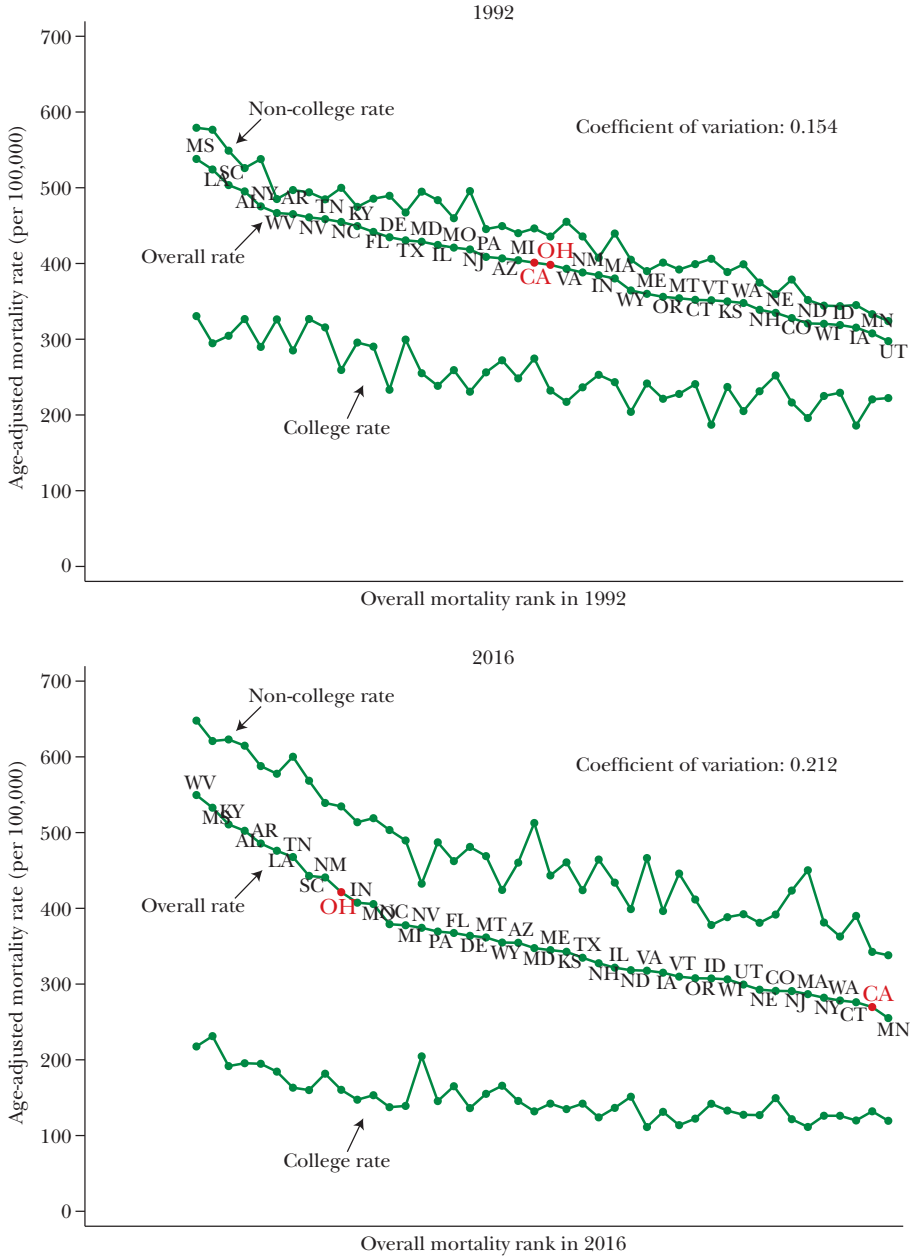
Figure 3 shows all-cause midlife mortality rates separately for 1992 and 2016 for each state, ranked from highest to lowest. The bottom line in each panel is the mortality rate for college-educated residents in each state, while the top line is for non-college; overall state mortality is approximately a weighted average of these two rates, with the weights reflecting the state's share of college-educated residents. Our mortality data come from the collection of individual-level detailed mortality records maintained by the National Center for Health Statistics (NCHS). These records, derived from death certificates, include the cause (or causes) of death for each decedent, as well as demographic information such as age, sex, race, education, and place of residence. Each mortality rate, then, is the number of total deaths divided by the relevant population calculated from the Current Population Survey (CPS) and the National Cancer Institute's Surveillance, Epidemiology, and End Results Program (SEER). To account for swings in mortality that would be expected from the aging of large cohorts, like the baby boomers, we age-adjust mortality rates to reflect the deaths that would occur given a fixed age distribution.[1] Starting in 1989, the US Standard Certificate of Death includes a field for the education level of the decedent. Most states were recording education level on death certificates by 1992; the coverage is generally better than 90 percent after 1990 and improves steadily over time.[2] For our cohort of focus, people aged 25 to 64, this is also the population for which the educational information for decedents is most accurate.

As the share of the population with college degrees has grown, overall mortality rates have moved closer to college-educated rates, as shown in Figure 3. The figure also displays the coefficient of variation for overall rates, which has risen from 0.154 to 0.212, an increase of more than one-third. In addition, Figure 3 illustrates the widening gap between college and non-college mortality, a result consistent with Case and Deaton's finding that educational differences in mortality are becoming

[1] We received permission from NCHS to use a restricted-use version of the detailed mortality files, which include state and county of residence, because this field is suppressed in public-use files after 2005. Age-adjustment is done by weighting the raw mortality rates of 10-year age groups in each state and year by shares of population that are constant across states and years. Specifically, the weights used are the standard 2000 reference population weights, drawn from Table V in the Technical Notes of NVSR's "Deaths: Final Data for 2017" (Kochanek et al. 2017).

[2] Four states began collecting education data on death certificates much later: Oklahoma in 1997, Georgia in 2010, South Dakota in 2004, and Rhode Island in 2015; as a result, we omit these states from the analysis. For the remaining states, like other research in this area, the lack of educational information for some decedents requires us to impute this information. Following Case and Deaton (2017), we do this based on the fraction in each education group by year, race, sex, age group, and cause of death; for all-cause mortality, we additionally impute based on state of residence.

Figure 3
Education and Midlife Mortality at the State Level: 1992 and 2016



Source: Authors' calculations using individual-level mortality data from the National Center for Health Statistics.
Note: The middle line in each panel (with accompanying state labels) depicts the all-cause mortality rate for all persons aged 25–64 in the given state and year. The top line depicts the mortality rate for persons in this age group who do not have college degrees, while the lower line depicts the midlife mortality rate of college graduates. Each panel also displays the coefficient of variation for overall mortality in the given year. All mortality rates are age-adjusted. For details, see the online Appendix.

more pronounced over time.[3] For example, in West Virginia and Kentucky in the upper left of the lower panel of Figure 3, all-cause mortality rose between 1992 and 2016 for non-college educated adults, while state-level college-educated mortality rates declined. There is also greater spatial variation in non-college graduate mortality rates, consistent with Chetty et al. (2016) who suggest that spatial variation in mortality is larger for people in lower income groups.

Most importantly, there was considerable movement in state-level mortality rankings between 1992 and 2016. We show a striking example by highlighting California and Ohio in each panel. In 1992, overall mortality rates for these two states were virtually identical. During the 1990s, however, the mortality experiences of the states diverged so that by 2016, the overall mortality rate in California was the second-lowest in the nation, while the rate in Ohio was the 10th highest.

The California–Ohio comparison is consistent with one of the hypotheses discussed earlier: mortality rates in high-education states such as California could have declined by more because of the national mortality trend favoring higher-educated people. We therefore want to ask whether health improved so much in California (and states like it) because these states initially had higher fractions of college-educated adults or because those fractions grew over time.

The role of education in driving mortality dispersion across states can be evaluated with a statistical model. In any given year, a state's overall mortality rate can be thought of as a weighted average of the individual mortality rates for its college-educated and non-college populations, with the weights for this average depending on the state's college-educated population share. In turn, we can think of the state's college mortality rate as the overall mortality trend for all college-educated Americans in that year, plus a state-and-year specific residual. Similarly, the state's non-college rate can be decomposed into the overall national mortality trend for college-educated Americans, plus an additional factor to capture the high (and rising) mortality penalty faced by non-college Americans, plus a non-college state-year residual. For a given year, we can thus characterize each state's mortality rate as:

$$\begin{aligned}
&\text{Overall state mortality rate (MR)} = (\text{state's college population share}) \\
&\quad \times (\text{national college mortality rate} + \text{state's college mortality rate residual}) \\
&\quad + (\text{state's non-college population share}) \\
&\quad \times (\underbrace{\text{national college mortality rate} + \text{national non-college mortality penalty}}_{\text{national non-college mortality rate}} \\
&\qquad + \text{state's non-college mortality-rate residual}).
\end{aligned}$$

[3]Our broad measures of college graduates and non-college graduates is likely to mask heterogeneity in educational attainment within these groups: for a discussion of heterogeneity in the non-college group, see Novosad, Rafkin, and Asher (2020).

This framework allows us to allocate the growing state-level divergence in mortality rates across four channels:

(a) *Changes over time in college population shares across states.* These changes could arise from state-level differences in college attendance or from differences in net migration rates of college-educated persons. Because college mortality rates are lower than non-college rates, changes in college shares across states could increase dispersion in overall state mortality.

(b) *An increase in the mortality penalty for Americans without a college education.* Holding college shares constant, the well-documented increase in the mortality penalty for non-college Americans would tend to raise relative mortality in states with relatively few college graduates.

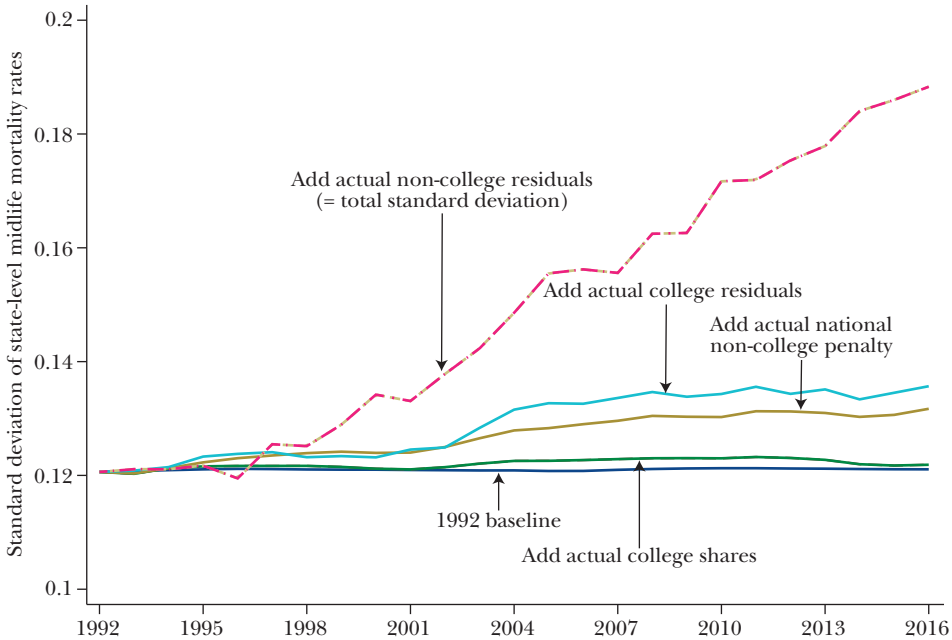
(c) *An increase in the standard deviation of the state-level mortality residuals for college residents.* This residual captures any difference between national and state mortality rates among college-educated persons. A gap between a state's college mortality rate and that of the nation could stem from the state's investments in health (interpreted broadly to include public and private health investments), taxes on products that impact health (such as tobacco and alcoholic beverages), and from differential health behaviors. For example, as information about nutrition, exercise, and tobacco's role in health increased, college graduates in states like California may have adopted healthy behaviors more often than college graduates in the nation as a whole.

(d) *An increase in the standard deviation of the state-level mortality residuals for non-college residents.* This term, similar to the college residual, captures the difference between state and national mortality rates among non-college adults. Also, like the college residual, the non-college residual will arise from state-specific policies, taxes, and behaviors that matter for mortality. Examples especially relevant for the non-college population include state-level minimum-wage legislation or the generosity of programs such as Medicaid. State regulations promoting clean air and water could also affect the non-college population disproportionately if these individuals tend to live in environmentally stressed communities.

Figure 4 shows how each of these channels contributes to the growth of state-level dispersion. On the vertical axis is the standard deviation of (log) mortality rates across states, with dispersion rising from 0.12 in 1992 to 0.19 in 2016. The baseline is a flat line because it holds all components of state mortality—college population shares, national mortality rates, and state-and-education specific residuals—constant at their 1992 levels. The other lines in the figure depict standard deviations of the log state mortality rates that are implied when the 1992 values of selected model components are replaced with their actual values. For example, replacing each state's 1992 college-educated population share with its actual evolving college shares (channel a) has only a modest impact on the implied standard deviation of log mortality rates across states, while replacing the 1992 national non-college mortality penalty with the rising actual values of this penalty (channel b) adds a bit more. Combined, however, these two channels account for less than one-sixth of the total increase in state-level standard deviation over time. Rising variation in

Figure 4

Decomposing the Rising Dispersion in State-Level Midlife Mortality Rates (1992–2016)



Source: Authors' calculations using individual-level mortality data from the National Center for Health Statistics.

Note: The dash-dotted line at the top of the figure depicts the actual population-weighted standard deviation of log midlife mortality rates at the state level. The solid line at bottom ("1992 baseline") depicts the constant standard deviation that would have resulted if each of the four components in the model described in the text had remained constant through 2016. The intermediate lines in the figure show the implied standard deviations after progressively adding each of the model's four components in the following order: actual college population shares, the actual national non-college mortality penalty, actual college mortality rate residuals, and actual non-college mortality rate residuals. The panel shows that changes in college shares and the national non-college penalty explain little of the rising standard deviation over time. Most of the increased dispersion is due to widening dispersion in non-college mortality rate residuals. For details, see the online Appendix.

the standard deviation of actual state-level college residuals (channel c) adds an additional 6 percent, but the lion's share is caused by the increase in the standard deviation of residuals for non-college residents (channel d), which accounts for over three-quarters of the overall dispersion.[4]

Why is the contribution of non-college residuals so high? In part, the non-college component is likely to account for a larger share of the standard deviation

[4]This counterfactual varies according to which variables are changed to actual values first, but in the online Appendix we show that our general results are robust to the order in which each channel is introduced.

simply because college-graduates are typically less than 30 percent of the total population.[5] That said, there is independent evidence that variation in mortality among less-educated or lower-income persons is an important reason why mortality rates vary so much geographically. Montez et al. (2019) study education and mortality from the 1980s through 2011, finding that educational differences in mortality across states grew primarily due to divergence among the less-educated groups. Also, Chetty et al. (2016) link mortality records with individual income data to show that across local labor markets, mortality rates vary more at the bottom of the income distribution than at the top.

Yet our model indicates that the geographical variance in non-college mortality rates is not the whole explanation for rising dispersion in state-level mortality. Nor is this rising dispersion a mechanical consequence of the worsening national mortality penalty faced by non-college Americans. Rather, the importance of both residuals in our framework of state-level mortality suggests that in some states, "place effects" have evolved over time to the benefit of both college and non-college residents, and these place effects turn out to be important in explaining why mortality has diverged over the last three decades. An important clue pointing to the importance of place effects is the high within-state correlation of non-college and college residuals produced by the model, which is relatively stable at around 0.70 in both 1992 and 2016. In an extension of this exercise described in the online Appendix, we show that assuming that each state's yearly place effect is an equally weighted average of its non-college and college residuals shows that place effects can explain much of the increased variance attributed to the two sets of residuals in Figure 4.[6] Results such as these suggest that understanding the role of place in health is a key to understanding rising dispersion in health outcomes over time.

Income and the Rising Divergence of State-Level Mortality Rates

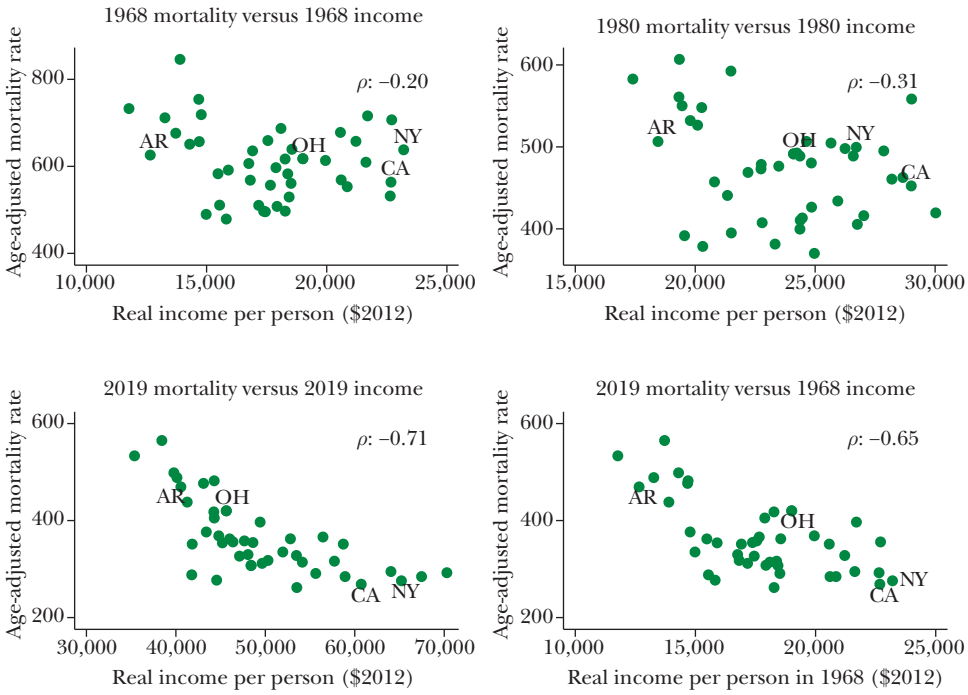
If place effects are large, one may reasonably ask whether other factors associated with mortality are mediated through these effects. An obvious candidate is income, which has been demonstrated at the micro-level to be an important predictor of early mortality (among many others, see Chetty et al. 2016).

In Figure 5, we plot state-specific midlife mortality rates against state-level per capita income in selected years. Our data on income is derived from Census Bureau estimates of total personal income received by the residents of individual states in each year. In this definition, income can include wages and salaries, profits from businesses and farms, payments due to ownership of financial assets, and government transfers, but not capital gains. Per capita income is defined as total personal income divided by state population as of July 1 of

[5] Additionally, because we base our model on the natural log of mortality rates, equal percentage changes in college and non-college rates, combined with higher average rates for non-college populations, will show up as a larger contribution of non-college rates to overall dispersion.

[6] Rather than using an equally weighted average of residuals to create place effects, an alternative method would be to use national shares of college and non-college graduates over the time period considered.

Figure 5
State-Level Income and Midlife Mortality Rates in Selected Years



Source: CDC Wonder database (https://wonder.cdc.gov/).
Note: Data are population-weighted statistics based on state-level age-adjusted mortality rates, defined as deaths per 100,000 persons. The coefficient of variation is the standard deviation of state-level mortality rates divided by the mean.

that year and expressed in 2012 dollars using the price deflator for personal consumption expenditures. Because the mortality rates are not broken down by education, we can rely on public-use mortality data and extend the analysis to 2019.

The upper left panel of the figure plots mortality against income in 1968. In this year, the correlation between mortality and per-capita state income was negligible at –0.20. Residents of New York and California in 1968 had higher average incomes than residents of Arkansas and Ohio (as they do currently), but in that year state-level mortality was similar across all four states. The upper right panel shows that in 1980, the correlation between income and mortality was largely unchanged, even as incomes grew. By 2019, however, state mortality rates had lined up largely in lockstep with income. The lower left panel shows a negative and significant correlation between income and mortality equal to –0.71.

At first glance, a strong correlation between income and mortality in the 2019 cross-section might suggest that changes in economic conditions (like income

or unemployment rates) predict changes in mortality. Instead, we find a more subtle pattern. The dramatic lining-up of income and mortality in the lower left panel of Figure 5 was not so much a shift in income rankings across states but rather a reshuffling of state-level place effects. Over time, midlife mortality has become increasingly correlated with the level of income, a result that, except for Pinkovskiy (2019), we had not previously seen. For example, during this period, mortality rates fell rapidly in New York and California while in Ohio and Arkansas they barely budged. Because high-income states in 2019 were typically high-income states in earlier years, we can express the lining-up of mortality and income with income data from previous years, as we do in the lower right panel of the figure. This panel shows that mortality in 2019 is also strongly negatively associated with state-level per capita income from more than 50 years earlier, with a correlation of –0.65. Taken together, these correlations strongly suggest that the greater dispersion of mortality levels across states is not being driven by the growing dispersion of income levels; that is, state-level changes in income do not explain state-level changes in mortality. This result is also supported by other analyses, including Case and Deaton (2017) and Ruhm (2018). Instead, mortality changes have been most favorable in those states that have tended to have high relative levels of income over the past three decades.

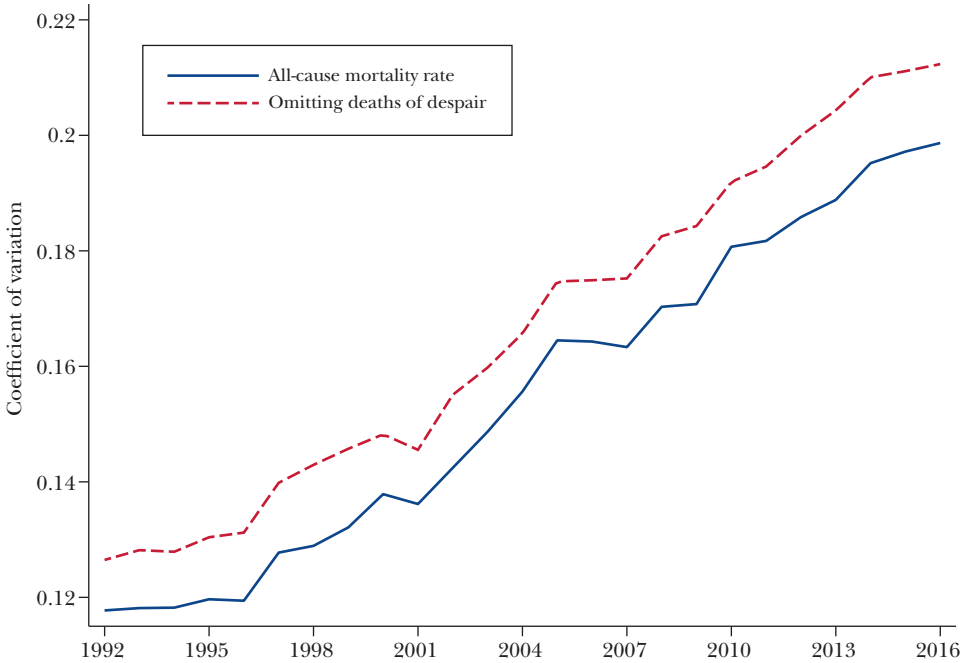
An obvious candidate to explain the growing correlation between midlife mortality and income is the growing rate of deaths of despair. Case and Deaton (2017) have not only documented the explosive increase in these deaths during the 21st century but have also shown that spatial dispersion of these deaths has risen dramatically over the same period. As they emphasize, the dramatic growth in midlife mortality is strongly correlated with education. Among college graduates, deaths of despair have remained largely unchanged and show little variation across states. By contrast, deaths of despair in the non-college population have risen sharply, with a particular impact in states such as West Virginia, New Mexico, Ohio, New Hampshire, and Massachusetts (Case and Deaton 2020). If deaths of despair have been concentrated in low-income states, then their recent growth could potentially explain the strengthening correlation between state-level income and mortality that we have documented.

Although deaths of despair have clearly contributed to the widening geographic disparity in mortality rates across states, they are not the primary cause. To see this, note that measured dispersion in midlife mortality has been growing rapidly even when deaths of despair are excluded from the analysis. Figure 6 depicts the coefficient of variation of midlife mortality rates with and without deaths of despair from 1992 to 2016. During this period, the coefficient of variation of mortality rates for deaths excluding deaths of despair increased by 67.9 percent, almost identical to the 68.7 percent increase in variation for all-cause mortality rates.[7]

[7] We acknowledge that deaths of despair are likely understated because of underreporting; a drug overdose might incorrectly be reported as a heart attack (Glei and Preston 2020; Vierboom, Preston, and Hendi 2019). However, the state-level correlation between the growth in deaths of despair, and in other deaths, is just 0.35, so biases are likely to be limited.

Figure 6

State-Level Mortality-Rate Coefficient of Variation with and without Deaths of Despair



Source: Authors' calculations using individual-level mortality data from the National Center for Health Statistics.

Note: Mortality rates are age-adjusted and correspond to persons aged 25-64. Deaths of despair are deaths attributed to cirrhosis (ICD9: 571; ICD10: K70, K73-74), suicide (ICD9: E950-959; ICD10: X60-84, Y87.0), or poisoning (E850-860, E980-982; ICD10: X40-X45, Y10-15).. The coefficients of variation are population-weighted. For details, see the online Appendix.

A key reason that deaths of despair do not completely explain rising dispersion is that even when accounting for their recent rapid growth, these deaths account for only about one-sixth of all deaths at midlife. (Deaths of despair do account for a larger fraction of life-years lost because such deaths tend to occur at younger ages.) The top panel of Figure 7 displays midlife mortality rates in selected years between 1992 to 2016 for deaths of despair and for four of the leading causes of death: cancer (more formally known as "malignant neoplasms"), heart disease, cerebrovascular diseases, and chronic lower respiratory diseases. Not surprisingly, deaths related to cancer and heart disease, the leading causes of death in the United States, are also the most common in 1992. Also notable is the dramatic reduction in death rates for these two diseases, as well as the well-documented (but still unexplained) slowdown in the reduction in heart disease deaths after 2008. Deaths of despair, while more common than cerebrovascular disease and chronic lower respiratory disease, were less common than cancer or heart disease deaths in 1992. By 2016, deaths of despair killed as many Americans aged 25–64 as did heart disease, but fewer than cancer.

The lower panel of Figure 7 displays the correlation between these causes of death and contemporaneous state income for the same years. Across all causes in the figure, state-level income became more negatively correlated with death rates from 1992 to 2016. Yet while income correlation for deaths of despair follows this pattern for most of the 1990s and early 2000s, the correlation later reverses course and becomes less negative. It is likely that the introduction of fentanyl and other synthetic opioids in recent years have changed the nature of the overdose crisis in the United States, weakening the correlation between state-level income and deaths of despair in the process.

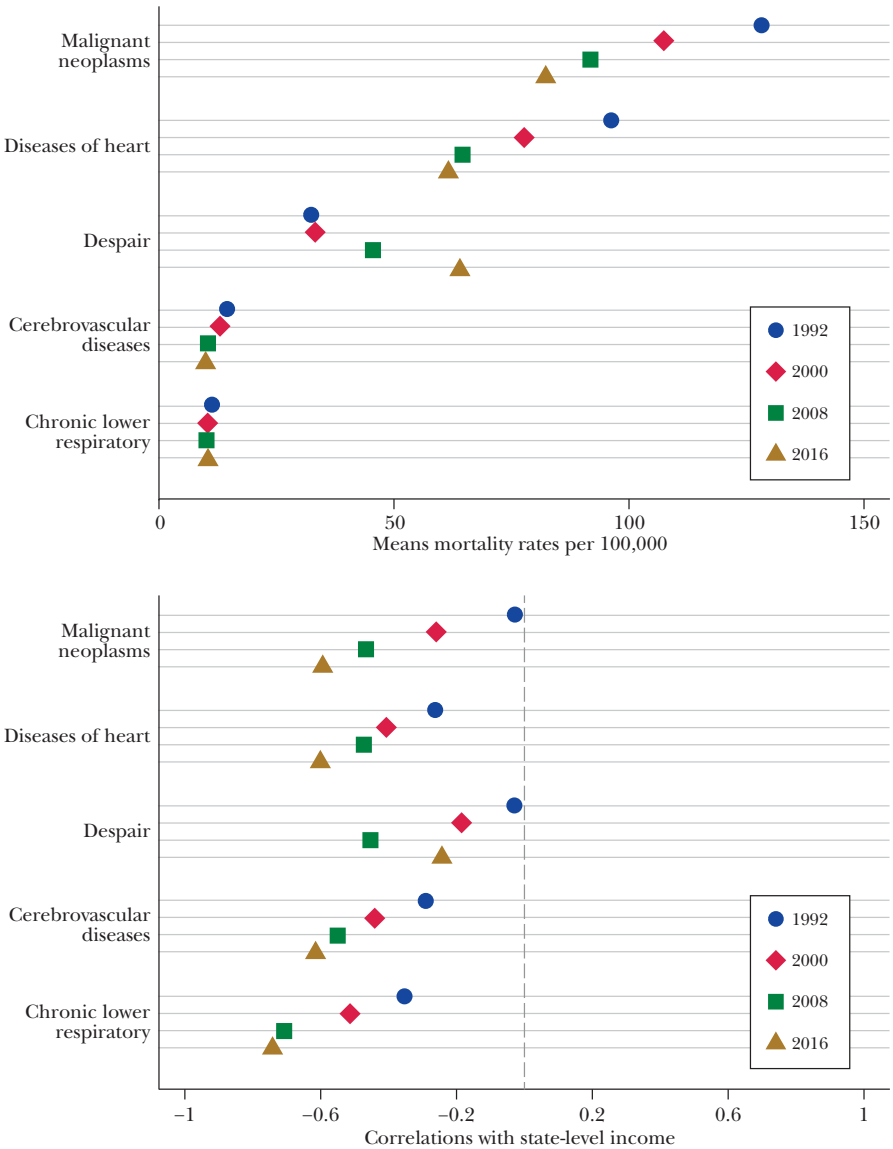
Our earlier example of Ohio and California from Figure 3 helps to illustrate how deaths of despair relate to overall patterns of mortality. As noted earlier, mortality rates in Ohio and California were similar in 1992 (401 deaths per 100,000 in California versus 398 in Ohio). Over time, deaths of despair grew by much more in Ohio so that by 2016, Ohio ranked third-highest among all states in these deaths. But overall mortality in Ohio did not change much over this period, as its large increase in deaths of despair (63 per 100,000) was nearly offset by a decline in other deaths (50 per 100,000). California, on the other hand, experienced a significant decline in overall mortality, to just 270 per 100,000 by 2016. This decline resulted from a small increase in deaths of despair (2 per 100,000) that was swamped by a decline in California's other deaths of 133 per 100,000—almost three times the fall in Ohio. All told, for these two states, deaths of despair accounted for about 40 percent of the widening gap, with the much greater decline in other deaths in California responsible for the remainder.

The ultimate relationship between opioid use, deaths of despair, and regional economic conditions is undoubtedly complex. Several papers have found that exogeneous shifts in manufacturing employment tend to raise adverse opioid-related outcomes (Autor, Dorn, and Hanson 2019; Pierce and Schott 2020; Charles, Hurst, and Schwartz 2018). However, the sizes of the estimated effects are too small to explain much of the massive increase in opioid deaths during the last several years, and some evidence suggests that reductions in manufacturing employment reduce mortality from other causes, such as heart disease (Pierce and Schott 2020). Additionally, regional patterns of deaths of despair are strongly influenced by factors that have little to do with changes in a region's economic conditions. These factors include the growing availability of high-grade heroin at low prices (Quinones 2016) or floods of cheap, illicit, and lethal fentanyl into some communities. Indeed, in the twelve months leading up to May 2020, California experienced an alarming surge in overdose deaths in particular communities (Kurle 2021).

When relating previous research on the economic determinants of health to our results in this section, two things are important to keep in mind. The first is that much of the earlier work relates changes in economic conditions to changes in health outcomes. This approach implicitly assumes a stable relationship between economic conditions and health; if incomes in an area decline, then health also declines due to the constant income-health relationship. But as Figure 5 shows, the income-health relationship itself is changing, as income becomes an increasingly powerful predictor of mortality. A second thing to remember is the long-run

Figure 7

Selected Mortality Rates by Cause and Their Correlations with State-Level Income over Time



Source: Authors' calculations using individual-level mortality data from the National Center for Health Statistics.

Note: Mortality rates are age-adjusted and correspond to persons aged 25–64. Means are population-weighted.Deaths of despair are deaths attributed to cirrhosis (ICD9: 571; ICD10: K70, K73-74), suicide (ICD9: E950-959; ICD10: X60-84, Y87.0), or poisoning (E850-860, E980-982; ICD10: X40-X45, Y10-15). The remaining causes of death are malignant neoplasms (ICD9: 140-208; ICD10: C00-C97), diseases of heart (ICD9: 390-398, 402, 404, 410-429; ICD10: I00-I09, I11, I13, I20-I51), cerebrovascular diseases (ICD9: 430-434, 436-438; ICD10: I60-I69), and chronic lower respiratory diseases (ICD9: 490-494, 496; ICD10: J40-J47).

nature of the disparities that we have analyzed. Health in richer states has been improving more than in poorer states for several decades, so the causes of this divergence likely run deeper than short-term fluctuations in employment or income. Case and Deaton (2017) make a similar point regarding deaths of despair, pointing out that neither state-level measures of income nor changes in income predict the recent rise in these deaths. In their view, deaths of despair are rising not because of short-term economic fluctuations, but rather, because of a long-run devaluation of work performed by persons without college degrees. Their recent book (Case and Deaton 2020) catalogs the devastating effects that this devaluation has had on America's social fabric during the last several decades.

To explain the long-run pattern of mortality differences across states—specifically the strengthening correlation between income and mortality—we also adopt a long-run perspective. In the next section, we contend that the association between state-level income and mortality is probably not a true causal relationship. Instead, the strengthening link between mortality and income reflects differences in regional resources, population behavior, and health-related policies that, over time, have contributed to larger mortality declines in richer states than in poorer ones.

A Portmanteau of State-Level Factors

Our framework for thinking about rising dispersion in state-level mortality has two main components. The first is that health in any point in time is largely determined by decisions made in the past, just as an economy's output of goods and services depends largely on the stock of physical capital built up by past investment. Indeed, health economists often use the concept of "health capital" to capture this phenomenon (Grossman 1972; Case and Deaton 2005). Individuals invest in health capital though behaviors such as regular exercise and maintaining a proper diet. Health capital depreciates over time at a rate that increases with age and in response to factors such as poor health behaviors, stress, and physically demanding occupations (Cutler, Meara, and Stewart 2020). The health-capital framework suggests that various factors have long-lasting effects that "come home to roost" in midlife mortality data many decades on. Given the evidence on the long lag time in health behaviors affecting mortality (Fenelon and Preston 2012), we should expect to observe smoking, obesity, pollution, and stress related to adverse economic conditions several decades ago to be gradually reflected in current midlife mortality (Preston, Vierboom, and Stokes 2018).

A second observation useful for understanding health dispersion is that states differ greatly in their health investment and depreciation rates. A classic example of this phenomenon is due to Victor Fuchs (1974), who observed that Utah exhibited much lower mortality than neighboring Nevada, despite similar levels of income, education, and access to health care. Fuchs argued that this gap could be explained by differing *behavior* in the two states, noting that rates of smoking, drinking, and family instability were much lower in Utah (where the majority of residents are members of the Mormon Church) than in Nevada. State-level differences in health investment

and depreciation rates can also be influenced by *policies* related to health. States that instituted high cigarette and liquor taxes or that expanded Medicaid under the Affordable Care Act might expect to see reduced rates of smoking and drinking and improved rates of health investment and depreciation among their residents.

Our hypothesis is that the widening divergence in midlife mortality and the tightening relationship between mortality and income reflect the long-run effects of varying behaviors and policies related to health capital during the last several decades. The data suggest that residents of high-income states have enacted policies and adopted behaviors with long-run payoffs to midlife mortality that are becoming increasingly apparent over time.

One question raised by this hypothesis is why health outcomes are diverging so much now—why hasn't health always been better in high-income states than low-income states? In 1992, high-income states were no more likely to experience lower mortality than low-income states. It was certainly not because high-income people at the time were sicker; individual-level analyses using data from the same period demonstrated a strong negative income gradient in mortality (Pappas et al. 1993), and a similar negative relationship between smoking and income was also apparent. Nor can lagged health effects explain this surprising result; unlike the strong link between 1992 income and current state-level mortality, there is only a weak association between state-level income in 1968 and mortality rates in 1992.

To explain why state differences in mortality have become more aligned with state-level variables like income after about 1990, we instead hypothesize that in the middle of the 20th century, social structures in low-income states provided more safeguards against adverse health outcomes. Perhaps more importantly, during this period there may have been more opportunities for risky behavior in high-income states. Black et al. (2015) show that African-Americans who migrated from the Deep South during the Great Migration experienced higher levels of mortality than those who stayed home, conditional on their initial health statuses. Although migrants may have had higher incomes in the North, "beneficial health benefits due to economic and social improvement were apparently swamped by other forces, such as changes in behavioral patterns that were detrimental to long-term health, including higher propensities to smoke and consume alcohol" (p. 501).[8] By the late 20th century, however, high-income states were more likely to enact health investments that over the next quarter-century resulted in more effective safety nets, more rapid diffusion of effective pharmaceutical treatments, a reduction in smoking, and a consequent decline in all-cause mortality (Montez et al. 2019, 2020; Miller and Wherry 2019; Buxbaum et al. 2020).

The hypothesis that investments related to Medicaid matter for the evolution of mortality has empirical support. Several authors, drawing upon different time periods and settings, show important evidence of plausibly causal reductions in

[8] Further evidence on the importance of state policies comes from Kansas, which imposed prohibition in 1880, not ending it until 1948. Perhaps not coincidentally, in 1959, Kansas was tied in first place for the state with the highest life expectancy.

mortality and morbidity linked to state differences in Medicaid policies. Owing to Medicaid eligibility's link with Aid to Families with Dependent Children, a program dating to 1935 (and commonly referred to as "welfare"), there was substantial cross-state variation in the shares of newborns eligible for Medicaid. Using that variation, Goodman-Bacon (2018) estimates that infant mortality fell for newborn cohorts after Medicaid's implementation in the 1960s and 1970s, and it did so in states with higher rates of eligibility for Medicaid. In the aggregate, nonwhite infant mortality fell by 11 percent in relation to Medicaid's implementation, and it did so for the causes of death amenable to medical intervention at that time (Goodman-Bacon 2018). Later expansions of Medicaid (in the late 1980s and early 1990s) to pregnant women and newborns with slightly higher incomes also coincided with reductions in infant mortality (Currie and Gruber 1996). States that expanded eligibility for Medicaid under the Affordable Care Act saw declines in mortality and morbidity among near-elderly adults (Miller, Johnson, and Wherry 2021).

Even more important for the time period we study, the implementation of Medicaid and its later expansions to pregnant low-income women have been linked to lower morbidity and mortality in the long run (Goodman-Bacon 2021; Miller and Wherry 2019). Again, using state variation in eligibility for Medicaid when first implemented due to its link to state participation in the Aid to Families with Dependent Children, Goodman-Bacon (2021) estimates: "Medicaid added 10 million quality adjusted life-years for cohorts born between 1955 and 1975 and saved the government more than twice its original cost" (p. 2588). This latter point is important since states share up to half the Medicaid program costs, so spending more crowds out other beneficial state spending. Later Medicaid expansions of the 1990s also had lasting effects, with infants whose mothers gained Medicaid coverage in the early 1990s experiencing lower rates of chronic conditions or hospitalizations for diabetes and obesity in adulthood (Miller and Wherry 2019).

Other health programs targeting low-income populations matter for the evolution of long-term health, too. Using variation in the opening of Community Health Centers in the 1960s and 1970s (designed to care for medically under-served populations), Bailey and Goodman-Bacon (2015) showed that age-adjusted mortality rates had declined by an additional 2 percent in counties that opened Community Health Centers compared to those that did not. Further, the mortality decline was driven by deaths to adults over age 50. This pattern we see is also consistent with the hypothesis suggested by Case and Deaton (2017) that cohorts entering the workforce in the 1970s and 1980s experienced a changed economic landscape, one which shifted particularly against people without college degrees.

Another important policy for health is environmental policy, since particulate pollution both sickens and kills, especially among vulnerable residents (Deryugina et al. 2019). A recent paper mapped changes in particulate pollution in the United States from 1980 to 2016, to show that particulate pollution has declined everywhere, though not necessarily equally (Colmer et al. 2020). Returning to our example of diverging mortality rates in Ohio and California, it is interesting that pollution declined by more in Ohio than in California during this time period; West Virginia experienced among the greatest improvement in air quality. Thus, policies

to reduce particulate pollution seem unlikely to explain this pattern of diverging mortality across states.

Whereas the empirical work cited so far in this section has investigated formal policies, a growing body of research examines differences in informal health-care practices across geographic areas. One example is the riskiness of prescriptions. Finkelstein, Gentzkow, and Williams (2019b) find that Medicare patients moving from regions with low levels of opioid prescriptions to regions with high levels are more likely to receive risky opioid prescriptions in their new communities. More generally, the question of whether the overall quality of health care has been converging or diverging across geographic areas during the past three decades is unresolved (Skinner and Staiger 2015). As discussed above, exposure to Medicaid improves long-term health outcome for children and adults, but quantifying how they explain the variation in this study is a subject of ongoing research.

All told, there is strong empirical support for the notion that specific health-related policies and behaviors differ across states, and that these differences matter for mortality. But quantifying how much of the total rise in state-level mortality dispersion can be explained by a health-capital model is more ambitious due to the long lags between investments and outcomes and the myriad types of policies and behaviors that might be relevant. It is even more difficult to quantify the separate contributions of policies versus behavior, given the likely feedback between these two "inputs" into the health-capital framework.

Even so, the health-capital model can help us understand some puzzles in the empirical literature. For example, one type of behavior—smoking—typically has a far larger effect on mortality than its direct clinical impact would predict (Cutler et al. 2011). Consistent with a broad health-capital model, Montez et al. (2019) observe that the outsized effect of smoking on health in area-level regressions can be understood by noting that changes in smoking behavior are often correlated with changes in health-related policies, including policies unrelated to smoking. In New York, for example, smoking rates in 1992 were 22.1 percent, about the same as North Dakota (21.9 percent) and only slightly below Mississippi (23.6 percent). By 2016, smoking had fallen to 9.2 percent in New York, compared to significantly smaller decreases in North Dakota (14.0 percent) and Mississippi (16.6 percent). Since the early 1980s, New York has imposed a substantial excise tax on cigarettes, which reached $4.35 per pack in 2016. But as Montez et al. argue, the higher cigarette tax in New York was part of a bundle of initiatives which, to one extent or another, tended to improve public health. For example, New York also participated in Medicaid expansion, implemented its own earned income tax credit, and set a minimum wage above the federal level ($9.00 per hour in 2016). In contrast, Mississippi has a negligible cigarette tax ($0.68 per pack in 2016), opted out of Medicaid expansion, does not offer its own earned income tax credit, and defaulted to the federal minimum wage. In addition, Mississippi has preempted local governments from implementing health-promoting legislation, such as paid sick days, a higher minimum wage, stricter firearm regulations, and nutrition labeling in restaurants.

To explore the plausibility of this explanation, we experimented with regressions with state-level mortality as the dependent variable and various explanatory

variables, including smoking and obesity rates. To capture state-level economic factors, we include state-level income, poverty rates, and manufacturing employment shares. We also include rates of prescribing effective or risky drugs, intended to capture health-care quality in 2008–2010 (Munson et al. 2013). Of course, these regression results should not be viewed as causal, and even interpreting the coefficients is tricky given the well-understood risks of using aggregated data to make inferences about individual causal factors.[9] Details of these regressions and the underlying data sources are available in the online Appendix.

Here, we simply note two general patterns that emerge. First, consistent with our earlier results on state-level income and mortality, income has a strong negative correlation with mortality in 2016 but no particular relation in 1992. However, when we include the additional control variables, the later income coefficient becomes much less negative. This reduction suggests that high-income states differ from low-income states along a variety of dimensions relevant for health, which are being captured in some ways by the additional controls.

Second, we find that the importance of smoking in these regressions is rising over time, even after controlling for income.[10] This is consistent with interpreting the state-level smoking rate as a "sentinel measure" of midlife mortality, with lower smoking rates reflecting a variety of public health efforts to encourage more healthy behavior. Indeed, one might view these evolving health-related factors proxied for by smoking as the dynamic equivalent of the static Utah-Nevada comparison by Fuchs (1974), in which behavior is influenced by policies, and vice versa.

Conclusion

We have documented a sharp increase in state-level disparities in midlife mortality, a result consistent with an emerging epidemiological literature (Vierboom, Preston, and Hendi 2019; Montez et al. 2019). This divergence has contributed to a more unequal America; West Virginia's midlife mortality rate is nearly double that in Minnesota. These widening geographic disparities in state-level mortality cannot be attributed to changing spatial patterns in education levels, income inequality, or rising deaths of despair. Instead, rising spatial inequality in midlife mortality results from some states experiencing dramatic overall declines in mortality across educational groups, while other states have experienced at best only modest progress. The first-order question is why high-income states have done so much better.

[9] This is sometimes referred to as the "ecological fallacy." As Gelman (2010) points out, the 15 poorest American states voted Republican in 2004, yet an analysis of individual-level data demonstrates a positive association between income and Republican voting.

[10] State-level smoking data come from the Behavioral Risk Factor Surveillance System (BRFSS) from the Centers for Disease Control and Prevention, an annual set of telephone surveys that collects state-level data on health behaviors. We use the BRFSS' post-stratification weights to construct state-level shares of daily smokers and obesity, where daily smokers are defined as respondents who reported smoking every day and having smoked at least 100 cigarettes throughout their lifetime. We also considered obesity, defined as having a body mass index greater than 30.0, but it was much less predictive of mortality. See the online Appendix for further details.

Our review of the evidence indicates that differential adoption of policies such as tobacco taxes, Medicaid expansions, and income support in high-income but not low-income states, have led to both widening spatial disparities in mortality and to an increasingly close negative association between income and mortality. These policies are distinct from but complementary to health-related behaviors that also differ across states.

We are certainly not the first to observe the importance of place for health, and there is a long-standing literature in geography and social epidemiology on the estimation and interpretation of place effects (McLafferty 2020). In the economics literature, there is a growing interest in estimating causal effects of place that abstract from selection effects that arise when, for example, people in poor health move to low-income neighborhoods lacking access to medical care (Jokela 2014). Studies of people who move can adjust for such selection, particularly when moves are randomized or exogenous (Chyn and Katz 2021). For example, randomized housing vouchers (Kling, Liebman, and Katz 2007; Ludwig et al. 2012) caused families receiving public housing vouchers to leave low poverty neighborhoods, while the destruction of large public housing projects (Chyn 2018) induced moves to lower poverty neighborhoods. Deryugina and Molitor (2020) examined older residents of New Orleans, many of whom moved after Hurricane Katrina in 2005. A notable finding was that average 8-year survival for all Medicare beneficiaries living in New Orleans in 2005 was two percentage points higher than expected in the absence of Katrina, even after accounting for residents who remained in New Orleans, or who died due to direct or indirect effects of the hurricane. In a companion paper in this volume, Deryugina and Molitor consider in more detail the mechanisms by which moving to a new region can affect longevity.

The causal place effects identified in the mover studies are conceptually different than the residual place effects we measure in our study; the short-term impact on health of moving from Mississippi to New York is different from the longer-term effects of growing up in Mississippi versus growing up in New York. For example, Finkelstein, Gentzkow, and Williams (2019a) found that the estimated causal effect of moving to a given region was often different from the underlying health of permanent residents. The cumulative effects of regional policies over the life-cycle—Medicaid coverage at birth, parental income support while a child, tobacco and alcohol taxes during adolescence, and higher-quality medical care during adulthood—are thus likely to exert a larger impact on life expectancy than the short-run impact of moving to a new neighborhood and changing physicians.

Going beyond mover studies to identify the determinants of place effects throughout the life cycle will be challenging. In particular, measuring the relative contributions of policies versus behavior on cross-state differences in health parallels the difficulty of disentangling effects of institutions versus culture on cross-country differences in income and wealth. Two proponents of the importance of institutions in development have observed that "England in the nineteenth century was . . . a very unhealthy place, but the government gradually invested in clean water, in the proper treatment of sewage and effluent, and eventually in an effective health service" (Acemoglu and Robinson 2012, p. 51). The authors interpret these

improvements not as the cause of England's rapid economic growth, but instead as a consequence of its economic success. Lessons from this literature on institutions have an encouraging policy implication: Although states with high income have shown the way, states with lower income capacity are not inexorably constrained to rates of midlife mortality that rank among the worst in developed countries.

■ *We are grateful to Anne Case, Angus Deaton, Amy Finkelstein, Matt Gentzkow, Erik Hurst, Heidi Williams, and especially Timothy Taylor for helpful comments and suggestions. Meara and Skinner are grateful for financial support from the National Institute on Aging (AG060104-01). The opinions expressed in this paper are those of the authors and do not indicate concurrence by the Federal Reserve Bank of Boston, the principals of the Board of Governors, of the Federal Reserve System.*

References

Acemoglu, Daron, and James A. Robinson. 2012. *Why Nations Fail: The Origins of Power, Prosperity, and Poverty.* New York: Crown Publishing Group.

Autor, David, David Dorn, and Gordon Hanson. 2019. "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men." *American Economic Review: Insights* 1 (2): 161–78.

Bailey, Martha J., and Andrew Goodman-Bacon. 2015. "The War on Poverty's Experiment in Public Medicine: Community Health Centers and the Mortality of Older Americans." *American Economic Review* 105 (3): 1067–1104.

Black, Dan A., Seth G. Sanders, Evan J. Taylor, and Lowell J. Taylor. 2015. "The Impact of the Great Migration on Mortality of African Americans: Evidence from the Deep South." *American Economic Review* 105 (2): 477–503.

Buxbaum, Jason D., Michael E. Chernew, A. Mark Fendrick, and David M. Cutler. 2020. "Contributions of Public Health, Pharmaceuticals, and Other Medical Care to US Life Expectancy Changes, 1990–2015." *Health Affairs* 39 (9): 1546–56.

Case, Anne, and Angus Deaton. 2005. "Broken Down by Work and Sex: How Our Health Declines." In *Analyses in the Economics of Aging,* edited by David A. Wise, 185–212. Chicago: University of Chicago Press.

Case, Anne, and Angus Deaton. 2015. "Rising Morbidity and Mortality in Midlife among White Non-Hispanic Americans in the 21st Century." *Proceedings of the National Academy of Sciences* 112 (49): 15078–83.

Case, Anne, and Angus Deaton. 2017. "Mortality and Morbidity in the 21st Century." *Brookings Papers on Economic Activity* 2017 (Spring): 397–476.

Case, Anne, and Angus Deaton. 2020. *Deaths of Despair and the Future of Capitalism.* Princeton, NJ: Princeton University Press.

Case, Anne, and Angus Deaton. 2021. "Life Expectancy in Adulthood Is Falling for Those without a BA Degree, but as Educational Gaps Have Widened, Racial Gaps Have Narrowed." *Proceedings of the National Academy of Science* 118 (11).

Centers for Disease Control and Prevention (CDC). n.d. "Behavioral Risk Factor Surveillance System (BRFSS)." US Department of Health and Human Services, Centers for Disease Control and Prevention.

Charles, Kerwin Kofi, Erik Hurst, and Mariel Schwartz. 2018. "The Transformation of Manufacturing and the Decline in US Employment." In *NBER Macroeconomics Annual 2018,* Vol. 33, edited by

Martin Eichenbaum and Jonathan Parker, 307–372. Chicago: University of Chicago Press.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler. 2016. "The Association between Income and Life Expectancy in the United States, 2001–2014." *JAMA* 315 (16): 1750–66.

Chyn, Eric. 2018. "Moved to Opportunity: The Long-Run Effects of Public Housing Demolition on Children." *American Economic Review* 108 (10): 3028–56.

Chyn, Eric, and Lawrence F. Katz. 2021. "Neighborhoods Matter: Assessing the Evidence for Place Effects." NBER Working Paper 28953.

Colmer, Jonathan, Ian Hardman, Jay Shimshack, and John Voorheis. 2020. "Disparities in PM2.5 Air pollution in the United States." *Science* 369 (6503): 575–78.

Currie, Janet, and Jonathan Gruber. 1996. "Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women." *Journal of Political Economy*, 104 (6): 1263–96.

Cutler, David M., Fabian Lange, Ellen Meara, Seth Richards-Shubik, and Christopher J. Ruhm. 2011. "Rising Educational Gradients in Mortality: The Role of Behavioral Risk Factors." *Journal of Health Economics* 30 (6): 1174–87.

Cutler, David M., Ellen Meara, and Susan Stewart. 2020. "Socioeconomic Status and the Experience of Pain: An Example from Knees." NBER Working Paper 27974.

Dartmouth Atlas Project. 2013. "The Dartmouth Atlas of Medicare Prescription Drug Use." Dartmouth College Report.

Deryugina, Tatyana, and David Molitor. 2020. "Does When You Die Depend on Where You Live? Evidence from Hurricane Katrina." *American Economic Review* 110 (11): 3602– 33.

Deryugina, Tatyana, and David Molitor. 2021. "The Causal Effects of Place on Health and Longevity." University of Illinois at Urbana-Champaign Report.

Deryugina, Tatyana, Garth Heutel, Nolan H. Miller, David Molitor, and Julian Reif. 2019. "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction." *American Economic Review* 109 (12): 4178–4219.

Fenelon, Andrew, and Samuel H. Preston. 2012. "Estimating Smoking-Attributable Mortality in the United States." *Demography* 49 (3): 797–818.

Finkelstein, Amy, Matthew Gentzkow, and Heidi L. Williams. 2019a. "Place-Based Drivers of Mortality: Evidence from Migration." NBER Working Paper 25975.

Finkelstein, Amy, Matthew Gentzkow, and Heidi L. Williams. 2019b. "What Drives Prescription Opioid Abuse? Evidence from Migration." NBER Retirement and Disability Research Center NB19-02.

Fuchs, Victor R. 1974. *Who Shall Live? Health, Economics and Social Choice.* New York: Basic Books.

Ganong, Peter, and Daniel Shoag. 2017. "Why Has Regional Income Convergence in the US Declined?" *Journal of Urban Economics* 102: 76–90.

Gaubert, Cecile, Patrick Kline, Dami´an Vergara, and Danny Yagan. 2021. "Trends in US Spatial Inequality: Concentrating Affluence and a Democratization of Poverty." NBER Working Paper 28385.

Gelman, Andrew. 2010. *Red State, Blue State, Rich State, Poor State: Why Americans Vote the Way They Do--Expanded Edition.* Princeton: Princeton University Press.

Glei, Dana A., and Samuel H. Preston. 2020. "Estimating the Impact of Drug Use on US Mortality, 1999-2016." *PLoS One* 15 (1).

Goodman-Bacon, Andrew. 2018. "Public Insurance and Mortality: Evidence from Medicaid Implementation." *Journal of Political Economy* 126 (1): 216–62.

Goodman-Bacon, Andrew. 2021. "The Long-Run Effects of Childhood Insurance Coverage: Medicaid Implementation, Adult Health, and Labor Market Outcomes." *American Economic Review* 111 (8): 2550–93.

Grossman, Michael. 1972. "On the Concept of Health Capital and the Demand for Health." *Journal of Political Economy* 80 (2): 223–55.

Harris, Kathleen Mullan, Steven H. Woolf, and Darrell J. Gaskin. 2021. "High and Rising Working-Age Mortality in the US: A Report from the National Academies of Sciences, Engineering, and Medicine." *JAMA* 325 (20): 2045–46.

Hollingsworth, Alex, Christopher J. Ruhm, and Kosali Simon. 2017. "Macroeconomic Conditions and Opioid Abuse." *Journal of Health Economics* 56: 222–33.

Jokela, Markus. 2014. "Are Neighborhood Health Associations Causal? A 10-Year Prospective Cohort Study with Repeated Measurements." *American Journal of Epidemiology* 180 (8): 776–84.

Kling, Jeffrey R., Jeffrey B. Liebman, and Lawrence F. Katz. 2007. "Experimental Analysis of Neighborhood Effects." *Econometrica* 75 (1): 83–119.

Kochanek, Kenneth D., Sherry L. Murphy, Jiaquan Xu, and Elizabeth Arias. 2017. "Deaths: Final Data for 2017." *National Vital Statistics Reports* 68 (9).

Kurle, Sydney. 2021. "The Silent Epidemic: Drug Overdose Deaths Surge in California Pre-Pandemic." *State of Reform*, January 15. https://stateofreform.com/featured/2021/01/the-silent-epidemic-drug-overdose-deaths-surge-in-california-pre-pandemic/.

Ludwig, Jens, Greg J. Duncan, Lisa A. Gennetian, Lawrence F. Katz, Ronald Kessler, Jeffrey R. Kling, and Lisa Sanbonmatsu. 2012. "Neighborhood Effects on the Long-Term Well-Being of Low-Income Adults." *Science* 337 (6101): 1505–10. Data Files.

McLafferty, Sara. 2020. "Place and Quantitative Methods: Critical Directions in Quantitative Approaches to Health and Place." *Health and Place* 6.

Meara, Ellen R., Seth Richards, and David M. Cutler. 2008. "The Gap Gets Bigger: Changes in Mortality and Life Expectancy, by Education, 1981–2000." *Health Affairs* 27 (2): 350–60.

Miller, Sarah, Norman Johnson, and Laura R. Wherry. 2021. "Medicaid and Mortality: New Evidence from Linked Survey and Administrative Data." *Quarterly Journal of Economics* 136 (3): 1783–1829.

Miller, Sarah, and Laura R. Wherry. 2019. "The Long-Term Effects of Early Life Medicaid Coverage." *Journal of Human Resources* 54 (3): 785–824.

Montez, Jennifer Karas, Jason Beckfield, Julene Kemp Cooney, Jacob M. Grumbach, Mark D. Hayward, Huseyin Zeyd Koytak, Steven H. Woolf, and Anna Zajacova. 2020. "US State Policies, Politics, and Life Expectancy." *Milbank Quarterly* 98 (3): 668–99.

Montez, Jennifer Karas, and Lisa F. Berkman. 2014. "Trends in the Educational Gradient of Mortality among US Adults Aged 45 to 84 years: Bringing Regional Context into the Explanation." *American Journal of Public Health* 104 (1): 82–90.

Montez, Jennifer Karas, Anna Zajacova, Mark D. Hayward, Steven H. Woolf, Derek Chapman, and Jason Beckfield. 2019. "Educational Disparities in Adult Mortality across US States: How Do They Differ, and Have They Changed since the Mid-1980s?" *Demography* 56 (2): 621–44.

Munson, Jeffrey, Nancy E. Morden, David C. Goodman, Luca F. Valle, and John E. Wennberg. 2013. *The Dartmouth Atlas of Medicare Prescription Drug Use*. Lebanon, NH: The Dartmouth Institute for Health Policy and Clinical Practice.

National Academies of Sciences, Engineering, and Medicine. 2021. *High and Rising Mortality Rates among Working-Age Adults*. Washington, DC: The National Academies Press.

Novosad, Paul, Charlie Rafkin, and Sam Asher. 2020. "Mortality Change among Less Educated Americans." https://paulnovosad.com/pdf/nra-mortality.pdf.

Pappas, Gregory, Susan Queen, Wilbur Hadden, and Gail Fisher. 1993. "The Increasing Disparity in Mortality between Socioeconomic Groups in the United States, 1960 and 1986." *New England Journal of Medicine* 329: 103–109.

Pierce, Justin R., and Peter K. Schott. 2020. "Trade Liberalization and Mortality: Evidence from US Counties." *American Economic Review: Insights* 2 (1): 47–64.

Pinkovskiy, Maxim. 2019. "Does US Health Inequality Reflect Income Inequality—or Something Else?" *Liberty Street Economics*, October 15. https://libertystreeteconomics.newyorkfed.org/2019/10/does-us-health-inequality-reflect-income-inequalityor-something-else/.

Preston, Samuel H., Yana C. Vierboom, and Andrew Stokes. 2018. "The Role of Obesity in Exceptionally Slow US Mortality Improvement." *Proceedings of the National Academy of Sciences* 115 (5): 957–61.

Quinones, Sam. 2016. *Dreamland: The True Tale of America's Opiate Epidemic*. London: Bloomsbury Press.

Ruhm, Christopher J. 2017. "Geographic Variation in Opioid and Heroin Involved Drug Poisoning Mortality Rates." *American Journal of Preventive Medicine* 53 (6): 745–53.

Ruhm, Christopher J. 2018. "Deaths of Despair or Drug Problems?" NBER Working Paper 24188.

Ruhm, Christopher J. 2019. "Drivers of the Fatal Drug Epidemic." *Journal of Health Economics* 64: 25–42.

Skinner, Jonathan, and Douglas Staiger. 2015. "Technology Diffusion and Productivity Growth in Health Care." *Review of Economics and Statistics* 97 (5): 951–64.

Vierboom, Yana C., Samuel H. Preston, and Arun S. Hendi. 2019. "Rising Geographic Inequality in Mortality in the United States." *SSM Population Health* 9.

Woolf, Steven H., and Heidi Schoomaker. 2019. "Life Expectancy and Mortality Rates in the United States, 1959–2017." *JAMA* 322 (20): 1996–2016.