NBER WORKING PAPER SERIES

AGGREGATION AND THE ESTIMATED EFFECTS OF LOCAL ECONOMIC CONDITIONS ON HEALTH

Jason M. Lindo

Working Paper 19042
http://www.nber.org/papers/w19042

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2013

I am extremely grateful to Eric Steinmann for exemplary research assistance. I also thank Ben Hansen, Doug Miller, Adriana Lleras-Muney, Marianne Page, Chris Ruhm, Jessamyn Schaller, Ann Huff Stevens, Glen Waddell, and Wes Wilson along with seminar participants at the University of Maryland, the University of Oregon, and the 2012 Meetings of the Society of Labor Economists for their thoughtful comments. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

Aggregation and The Estimated Effects of Local Economic Conditions on Health
Jason M. Lindo
NBER Working Paper No. 19042
May 2013
JEL No. E32,I10,J20

ABSTRACT

This paper considers the relationship between local economic conditions and health with a focus on different approaches to geographic aggregation. After reviewing the tradeoffs associated with more- and less-disaggregated analyses–including an investigation of the migratory response to changing economic conditions–I update earlier state-level analyses of mortality and infant health and then consider how the estimated effects vary when the analysis is conducted at differing levels of geographic aggregation. This analysis reveals that more-disaggregated analyses severely understate the extent to which downturns are associated with improved health. Further investigation reveals that county economic conditions have an independent effect on mortality but that state and regional economic conditions are stronger predictors. I also leverage county-level data to explore heterogeneity in the link between county economic conditions and health across states, demonstrating that local downturns lead to the greatest improvements in health in low-income states.

Jason M. Lindo
Department of Economics
University of Oregon
Eugene, OR 97403-1285
and NBER
jlindo@uoregon.edu

1 Introduction

Although Harvey Brenner's pioneering research suggested that health deteriorates during recessions (1973, 1975, 1979), follow-up work has revealed that estimates based on aggregate time-series data are quite fragile (Forbes and McGregor 1984; McAvinchey 1988; Joyce and Mocan 1993; Laporte 2004; Gerdtham and Johannesson 2005). As Ruhm (2000) points out, this "fragility is not surprising since any lengthy time-series is likely to suffer from substantial omitted variables bias."[1] In order to overcome such biases, researchers have since focused on panel approaches that exploit local variation in economic conditions. Specifically, this "area approach" estimates how an area's health changes *over and above changes occurring across all areas* when its economic conditions change *over and above changes occurring across all areas* and routinely reveals that health *improves* during recessions. With few exceptions, nearly all such studies using US data define "area" as a state.[2] Should we prefer estimates that use state-level data to estimates that use finer or broader definitions of area?

There are several tradeoffs to consider when choosing the level of geographic aggregation. First, a more-disaggregated approach allows one to explore heterogeneity more fully. For example, we may wish to know whether local economic conditions are more-strongly related to health for those who live in New York or for those who live in Louisiana. Since a time-series analysis of each state is unlikely to be very compelling for the reasons described above, we can only answer this question in a convincing fashion by disaggregating the data to a finer level so that the area approach can be applied to each state. In addition, more-disaggregated data makes it possible to separately identify the effects of local versus broader economic conditions.

Another benefit to taking a more-disaggregated approach is that it can improve power. In particular, it can leverage variation in economic conditions that may be masked in more-aggregate measures as contractions in some areas are offset by expansions in others.

At the same time, it is important to keep in mind that economic indicators are subject to measurement error, which is especially problematic for fixed-effects estimators (Griliches 1977; Griliches and Hausman 1986). The most common measure of economic conditions used in this literature is the unemployment rate, produced by the Bureau of Labor Statistics (BLS).

[1]For example, it is problematic for this approach that penicillin became increasingly available as the United States began to recover from the Great Depression.

[2]To my knowledge, the only exceptions are Currie and Tekin (2011) who consider foreclosures at the zip-code level in four states and Dehejia and Lleras-Muney (2004) who consider unemployment rates and supplement their state-level analysis with a county-level analysis of California.

However, as one considers smaller areas, one needs to be more and more concerned about measurement error in unemployment rates since they are based in part on household surveys (Bartik 1996; Hoynes 2000).[3] For this reason, employment-to-population ratios are preferable because they are based solely on administrative data. Still, one may have concerns about measurement-error bias that may be influenced by the level of aggregation.

It is also important to consider the fact that migration is influenced by economic conditions (Blanchard and Katz 1992; Saks and Wozniak 2011), particularly among highly-educated individuals (Bound and Holzer 2000; Glaeser and Gyourko 2005; Wozniak 2010; Notowidigdo 2011). This heterogeneity implies that the estimated improvements in health associated with recessions will understate the true improvements in health if standard demographic controls do not fully capture these sorts of compositional changes. That said, it is unknown whether education and other characteristics associated with health are more- or less-strongly related to the unemployment-migration relationship when one considers different types of moves and different definitions of local economic conditions. As such, it is unclear whether this sort of composition bias is likely to be of greater or lesser concern for more-disaggregated analyses.[4]

Given the complexity of these issues, I take as my starting point that it is not at all clear what level of geographic aggregation is preferred but that the tradeoffs deserve consideration and that much can be learned by comparing the results of alternative approaches. As such, after briefly reviewing the related literature (Section 2), I describe the different ways that I define areas throughout the subsequent sections (Section 3). I then explore the extent to which the migratory response to changes in economic conditions differs across socioeconomic status and different approaches to defining areas using restricted-use data from the Panel Study of Income Dynamics (Section 4). Next I replicate and update earlier state-level estimates of the relationship between economic conditions and mortality (Ruhm 2000 and Stevens et al. 2011) and the relationship between economic conditions at the time of conception and infant health (Dehejia and Lleras-Muney 2004) before considering how estimated effects vary when the analysis is conducted at differing levels of geographic aggregation (sections 5 and 6). I

[3] Angrist and Krueger (1999) provide intuition: “errors tend to average out in aggregate data.” Another problematic aspect of unemployment rate data is that the BLS’s substate estimates prior to 1990 are no longer considered “official BLS data” because they have not been revised to be consistent with the BLS’s current estimation procedure.

[4] The systematic outmigration that occurs when an area’s unemployment rises also highlights the importance of well-measured population denominators in calculating mortality rates—population measures that do not account for the systematic outmigration caused by economic downturns will lead to mechanical reductions in mortality rates.

then leverage county-level data to gain additional insights into the economic-conditions-health relationship by simultaneously estimating the effects of county, state, and regional economic conditions; by obtaining separate estimates of the effects of county economic conditions for each state; and by exploring whether heterogeneous effects on health outcomes across states can be explained by state characteristics (Section 7).

My main findings are as follows:

1. High school graduates and those with relatively-high permanent incomes are disproportionately likely to leave an area in response to a local downturn—there is not strong evidence that this empirical regularity differs across different definitions of areas.

2. The estimated link between economic conditions and adult mortality is highly sensitive to the level of geographic aggregation, with more-disaggregated analyses routinely producing estimates that are smaller in magnitude. Estimates that simultaneously consider the effects of county, state, and regional economic conditions suggest that this is because broader measures of economic conditions are stronger predictors of health outcomes.

3. State-specific estimates based on county-level data reveal that local downturns cause mortality to fall across a majority of the United States, but that there is substantial heterogeneity. Moreover, local downturns appear to lead to the greatest improvements in health in low-income states.

2 Related Literature

Studies exploring the relationship between economic conditions and health tend to fall into one of two categories: those that focus on the effects of the specific economic circumstances that an individual faces (income, employment status, etc.) and those that focus on the effects of (usually local) macroeconomic conditions. One of the somewhat-puzzling aspects of this broad and extensive literature is that job loss leads to poorer health among those losing their jobs and their families (Sullivan and von Wachter 2009; Kuhn, Lalive, and Zwelmuller 2009; Eliason and Storie 2009a, 2009b; Lindo 2011; Black, Devereux, and Salvanes 2012) while health improves during recessions in developed countries (Ruhm 2000, 2003, 2005, 2007; Dehejia and Lleras-Muney 2004; Johansson 2004; Neumayer 2004; Tapia Granados 2005; Gerdtham and Ruhm 2006; Lin 2009; Miller et al. 2009; Stevens et al. 2011).

While many authors note that these two results are not necessarily contradictory, it has yet to be demonstrated precisely why and how they co-exist, and what that implies for our understanding of broader questions regarding employment and health. Nonetheless, this context is important for the interpretation of the results that follow. In particular, in order to reconcile these two strands of literature, it must be the case that macroeconomic conditions affect health through mechanisms besides one's own employment status. For example, they may affect an individual's health via impacts on pollution (Chay and Greenstone 2003), the quality of care (Stevens et al. 2011), traffic congestion, uncertainty about one's future employment, the availability of overtime, etc.

3 Defining Areas

Throughout my analyses, I separately identify the effects of unemployment using data at five different levels of geographic aggregation, from counties to regions. Except where replicating earlier research, all of my analyses are based on data that are available at the county level to ensure that all estimates are based on the same underlying sample. In particular, I do not use data from: Alaska or Hawaii where county population data (described in greater detail below) are unavailable prior to 1990; counties without at least one person of each age (0–85) in 1990 so that age-adjusted mortality rates can be calculated at the county level; Virginia where there have been substantial changes to county definitions over time; the Great Lakes region in 1976 where BLS data for Illinois counties are unavailable; or the Southeast region in 2005 and 2006 where BLS data for several Louisiana counties are unavailable.[5] Section 5 demonstrates the trivial impact these sample restrictions have on the estimated effects of unemployment on health.

My most-aggregated analyses use region-level data based on the eight regions defined by the Bureau of Economic Analysis (BEA): New England, Mideast, Great Lakes, Plains, Southeast, Southwest, the Rocky Mountain, and Far West.[6] These BEA regions were developed in the

[5]In an additional an additional effort to achieve consistency in the data over time, for all years I combine the counties of La Paz and Yuma (Arizona) which split in 1983; Washabaugh and Jackson (South Dakota) which merged in 1983; and Adams, Boulder, Jefferson, and Weld (Colorado) from which Broomfield split off in 2001.

[6]The state groupings are as follows. *New England:* Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont. *Mideast:* Delaware, District of Columbia, Maryland, New Jersey, New York, Pennsylvania. *Great Lakes:* Illinois, Indiana, Michigan, Ohio, Wisconsin. *Plains:* Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota. *Southeast:* Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, Virginia, West Virginia. *Southwest:* Arizona, New Mexico, Oklahoma, Texas. *Rocky Mountain:* Colorado, Idaho, Montana, Utah, Wyoming. *Far West:* Alaska, California, Hawaii, Nevada, Oregon, Washington.

1950s with the intention of grouping states with similar economic economic and social factors.[7]

My next most-aggregated analyses use state-level data, followed by analyses that use data at the BEA-Economic-Area level. The mapping of counties to BEA Economic Areas is depicted in Figure 1. Johnson and Kort (2004), who provide a detailed account of the BEA's procedure, describe the 179 BEA Economic Areas as follows:

> "[They] define the relevant regional markets surrounding metropolitan or micropolitan statistical areas. They consist of one or more economic nodes—metropolitan or micropolitan statistical areas that serve as regional centers of economic activity—and the surrounding counties that are economically related to the nodes. These economic areas represent the relevant regional markets for labor, products, and information. They are mainly determined by labor commuting patterns [based on the decennial census] that delineate local labor markets and that also serve as proxies for local markets where businesses in the areas sell their products. In less populated parts of the country, newspaper readership data are also used to measure the relevant regional markets."

I also conduct analyses using data at the BEA-Component-Economic-Areas level. Component Economic Areas are much the same as Economic Areas except they can be based on fewer counties and fewer residents.[8] Last, as mentioned above, I conduct analyses based on data at the county level. Naturally, the sample restrictions described above reduce the number of states, Economic Areas, Component Economic Areas, and counties below the number that exist.

4 Economic Conditions, Migration, and Socioeconomic Status

In this section, I explore how the migratory response to economic conditions varies across socioeconomic status. This analysis is intended to provide context to the sections below where estimates of the effects of local economic conditions on health rely on the assumption that readily available control variables are sufficient to capture the effect of economic conditions on the composition of residents in an area (as the composition relates to health).

[7]In contrast, the five regions used in the United States census were developed in the 1880s with similar intentions.

[8]For example, a Component Economic Area would be considered too small to form an Economic Area if it consisted of fewer than three counties and fewer than 500,000 employed residents. Also note that 167 of 344 Component Economic Areas are sufficiently large that they also serve as independent Economic Areas; the remaining 177 combine to create the remaining 12 Economic Areas.

For this analysis, I use the entire sample of individuals in the PSID from 1968 to 1997 who are above 23 years old, with the exception of the special "Latino Sample" that was surveyed from 1990 to 1995.[9] Migration across areas is measured by an individual's residential location each year. For example, if an individual reports living in California one year and Oregon the next, they are coded as having moved states but are coded as *not* having moved to a new BEA region.[10]

In order to estimate the effect of economic conditions on migration, I use the following linear-probability model

$$Move_{it} = Epop_{it}\beta + \alpha_t + \gamma_i + u_{it}, \tag{1}$$

where $Move_{it}$ is an indicator variable that takes a one if an individual moves areas before the next year, $Epop_{it}$ is the employment-to-population ratio in an individual's area in the current year calculated using county-level employment counts from the BLS and population counts from the National Cancer Institute's Surveillance, Epidemiology, and End Results Program (SEER), α_t are year fixed effects, γ_i are individual fixed effects, and u_{it} is a random error term that is allowed to be correlated across t within i.[11] The individual fixed effects control for the possibility that certain types of individuals may be more mobile and also tend to live in areas with strong economies.

In order to explore heterogeneity across socioeconomic status, I use the following linear-probability model

$$Move_{it} = Epop_{it}\beta + (Epop_{it} \times SES_i)\phi + \alpha_t + \gamma_i + u_{it}, \tag{2}$$

where SES_i is a measure of socioeconomic status and the estimate of ϕ will reveal the extent to which the economic-conditions-migration gradient varies across socioeconomic status.

The results of this analysis are shown in Table 1. Column 1, which simply considers the effect of local economic conditions on migration, indicates that individuals are more likely to move out of an area when its economic conditions worsen, whether one defines areas as a states, BEA Economic Areas, BEA Component Economic Areas, or counties. That said, the results of this analysis indicate that individuals are *less* likely to move regions when regional economic

[9] After 1997, the PSID changed to a biennial format.

[10] In order to examine moves across BEA Economic Areas, BEA Component Economic Areas, and counties, I use the PSID's restricted-use Geocode Match files.

[11] SEER population estimates are based on an algorithm that incorporates information from Vital statistics, IRS migration files and the Social Security database.

conditions worsen. Though this difference is interesting, for the purposes of understanding the link between economic conditions and health, documenting whether migratory responses are heterogeneous across individual characteristics that are known to be associated with health outcomes is of primary concern. For this purpose, I focus on two measures of socioeconomic status that cannot be reliably measured for small-area populations that can be measured using the PSID: high school education and permanent income decile. The measure of education is based on whether an individual has 12 or more years of education. An individual's permanent income is based on their average residuals from a regression of incomes on age and year fixed effects interacted with gender.[12] Consistent with earlier research, the estimates in columns 2 and 3 routinely indicate that high-socioeconomic-status individuals are more likely to leave an area when it experiences an economic downturn. Thus, the area approach to estimating the effects of unemployment on health will likely understate the improvements in health caused by economic downturns if the typical battery of demographic controls does not fully capture these compositional changes. Of particular relevance to the analyses that follow, there is not strong evidence that behavioral difference differs across different definitions of areas. As such, it seems unlikely any migration-induced bias would generate differences in the economic-conditions-health relationship when the analysis is conducted at different levels of geographic aggregation.[13]

5 Methodology and Updates to Earlier Research

Before presenting estimates of the link between local economic conditions and health outcomes using different definitions of areas in the next section, in this section I present the estimated effects from prior state-level studies, adapt the estimation strategies in a way that allows more-disaggregated analyses, consider how these changes alter the estimates, and then extend the analyses to include additional years of data. I begin by focusing on mortality outcomes and then turn to infant health outcomes.

[12]Only years in which an individual is less than 62 years old and is the head of household or the 'spouse' of the head of the household (as defined by the PSID) are used for this calculation.

[13]Though racial composition can be measured reasonably well for small areas, I have also investigated the extent to which there are racial differences in the migratory response to changing economic conditions. These estimates reveal that whites are more likely to leave an area in response to downturns than non-whites, except when considering moves across counties in response to changing county-level economic conditions.

5.1 Mortality

In his highly influential study, Ruhm (2000) considers the effects of macroeconomic conditions on health using mortality rates from Vital Statistics of the United States publications and estimates of the unemployment rate from the BLS. In order to focus on within-area variation, Ruhm's estimates are based on the regression equation

$$H_{at} = E_{at}\beta + X_{at}\delta + \alpha_t + \gamma_a + \theta_a t + \epsilon_{at}, \tag{3}$$

where H_{at} is a measure of health for area a in year t, E_{at} is a measure of economic conditions, X_{at} is a vector of time-varying controls, α_t are year fixed effects, γ_a are area fixed effects, and $\theta_a t$ are area-specific time trends. To operationalize this identification strategy, Ruhm defines a as a state, H_{at} as the natural log of the mortality rate (deaths per 100,000), E_{at} as the unemployment rate, and X_{at} includes the fraction of the state population that is: less than five years old, 5–64 years old, greater than 64 years old, black, hispanic, a high school dropout, has some college, is a college graduate.[14] In Column 1 of Table 2, I display the estimate based on these data and definitions while clustering the standard error estimate on the state.[15] The point estimate indicates that a one-percentage-point increase in the unemployment rate is associated with a 0.54-percent decrease in overall mortality.

As the starting point for my analysis, I begin with the approach used in Stevens et al. (2011) who extend Ruhm (2000) in several ways. First, they create mortality rates using death counts from Vital Statistics' micro-record multiple-cause-of-death files and population data from SEER (described above). Second, they pool monthly Current Population Survey data in order to construct overall unemployment rates and unemployment rates for separate demographic groups, which requires them to focus on data from 1978–2006. Third, they include a richer set of controls for the fraction of a state's population in various age brackets (less than 5, 5–17, 18–30, greater than 64) using the aforementioned population data, construct the fraction black with the aforementioned population data, and use CPS data to measure the fraction Hispanic and the fraction in each education group.[16] Last, they replace the natural log of the mortality rate with the natural log of the *age-adjusted* mortality rate to account for uneven changes in

[14] These control variables are calculated by interpolating between decennial censuses. Additionally, estimates are weighted by the population in each state.

[15] As Ruhm (2000) did not present estimates that clustered standard errors, this estimate is taken from Stevens et al. (2011) who replicate and extend Ruhm's analysis.

[16] The fraction in each age group is based solely off of individuals who are at least 25 years old.

the age distribution across states. The age-adjusted mortality rate is calculated by taking the weighted average of the mortality rate for each age, using as weights the fraction of individuals in each age category in the US in 1990. After making these changes, their estimate (shown in Column 2 of Table 2) indicates that a one-percentage-point increase in the unemployment rate is associated with a 0.33-percent decrease in overall mortality.

In columns 3 through 9 of Table 2, I progressively make changes to this estimation strategy, ultimately arriving at an approach that can also be used in more-disaggregated county-level analyses. These changes are as follows:

- Use state-level unemployment rates published by the BLS for convenience. This change has no impact on the estimated effect (Column 3).

- Omit controls for the fraction Hispanic and the fraction in each education category, which cannot be reliably measured for small counties. This change has no impact on the estimated effect (Column 4).

- Add data from 1976, 1977, and 2007 to the analysis. Incorporating the earlier years of data has a substantial impact on the estimate, causing it to fall from -0.0033 to -0.0044 (Column 5). Adding 2007 data to the analysis has only a small impact on the estimate (Column 6).

- Restrict the sample to individuals living in counties with at least one person of each age (0–85) in 1990 so that age-adjusted mortality rates can be calculated at the county level. Also, omit data from Alaska and Hawaii where county codes are unavailable in the early years of the data and from Virginia where there have been substantial changes to county definitions over time. So that the unemployment rates correctly correspond to the counties contributing to the state-level estimates, use county-level BLS data to construct unemployment rates. These changes have a negligible impact on the estimate (Column 7).

- Use the death rate as the outcome variable rather than the log of the death rate, which may be undefined in small counties. The semi-elasticity based on this estimate (Column 8), calculated by dividing coefficient estimate by the mean of the outcome, is somewhat larger than the direct estimate in obtained in Column 7.

- Use the employment-to-population ratio as the measure of economic conditions. The semi-elasticity based on this estimate (Column 9) is smaller than the semi-elasticity for unemployment rates.

5.2 Infant Health

Like Ruhm (2000), Dehejia and Lleras-Muney (2004) conduct a state-level analysis—also characterized by Equation 3—but instead focus on various measures of *infant* health and the effects of economic conditions at the time of conception. As their primary outcome measures, they consider the fraction of children who have low birth weight (less than 2500 grams) and the fraction who have very low birth weight (less than 1500 grams), calculated at the race-by-state-by-year level based on vital statistics birth records for white and black mothers at least 18 years old. As their primary measure of economic conditions, they use state unemployment rates in the year of conception, which they base on the timing of the mother's last menstrual period. Column 1 of Table 3 displays their estimates, which indicate that a one-percentage-point increase in the unemployment rate reduces the incidence of low birth weight 0.26 percent and reduces the incidence of very low birth weight by 0.54 percent.[17]

In columns 2 through 9 of Table 3, I progressively make changes to the estimation strategy, ultimately arriving at an approach that can also be used in more-disaggregated county-level analyses. In Column 2, I instead define a child's year of conception as nine months prior to birth and include in the analysis children born to mothers for whom information on the last menstrual cycle is missing. The subsequent columns progressively include children classified as "other race" to the analysis and an indicator variable for "other race" to the regression model (Column 3); include children born to mothers of all ages (Column 4); collapse the state-by-year-by-race level data to the state-by-year level while adding controls for the fraction in each race category (Column 5); control for the age distribution of mothers with variables corresponding to the fraction of mothers who are less than 18 years old, 18–22 years old, 23–28 years old, and 29–34 years old (Column 6); update the sample to include data from 2000–2006 (Column 7); and then construct the sample based on data available at the county level, i.e., omitting data from Alaska, Hawaii, and Virginia for the reasons described above (Column 8). These changes tend to have only minor impacts on the estimated effects with one exception. When the data is extended from 1976–1999 to 1976–2006 the estimated effect of unemployment increases by

[17] Estimates are weighted by the number of births in each cell and standard-error estimates are clustered at the state level.

approximately 60 percent, suggesting that effect of economic conditions on newborn health has grown over time. Column 9 indicates that using the employment-to-population ratio as the measure of economic conditions produces similar results.

6 Estimates of the Unemployment-Health Relationship Using Different Definitions of Area

In this section, I explore how the estimated effects of economic conditions on health outcomes vary with different levels of geographic aggregation using the identification strategy described in the previous section. Though the convention in this literature is to cluster standard errors at the area level, to the extent to which the errors may be correlated for adjacent areas, it may instead be appropriate to cluster on broader areas where possible, e.g., clustering on regions for state-level analyses. That said, it turns out that the standard error estimates based on the conventional approach are either identical to or more conservative than estimates that cluster on broader areas, except when the analysis is conducted at the county level. For county-level estimates, clustering the standard errors at the state level yields the most conservative estimates. As such, I use this approach where applicable.

Column 1 of Table 4 focuses on how the estimated effects of economic conditions on overall mortality varies with different levels of geographic aggregation across panels A through E. Using the broadest definition of area, region, the estimate indicates that a one-percentage-point increase in the employment-to-population ratio is associated with a 0.51-percent increase in mortality. As we progressively consider more narrowly defined areas, there is a monotonic decline in the magnitude of the estimated effect. In particular, the point estimate shrinks by 25 percent as we move from the region level to the state level; shrinks another 18 percent as we move to the BEA-Economic-Area level; shrinks another 6 percent as we move to the BEA-Component-Economic-Area level; and then shrinks another 69 percent as we move to the county level. At the county level, the estimate indicates that a one-percentage-point increase in the employment-to-population ratio is associated with a 0.09-percent increase in mortality. Although this estimate is less than a third of the estimate based on state-level data, it remains highly significant at conventional levels.

Columns 2 through 4 take a similar approach but separately estimate the effects on youth mortality (age 0–17), working-age mortality (age 18–64), and elderly mortality (age 65+). This exercise is motivated by Miller et al. (2009) who explain that, even though unemployment has a similar percentage impact on younger and older individuals, the additional deaths that tend to be observed during recessions largely consist of the elderly because their baseline mortality rate is so high. Again, the magnitudes of the estimates are smaller in more-disaggregated analyses.

Finally, columns 5 through 8 show estimated effects on five major causes of death: cardiovascular problems, cancer, disease (including respiratory, infections and immune deficiencies, degenerative brain diseases, and kidney problems), motor-vehicle accidents, and suicides.[18] Echoing earlier work, these estimates reveal that local downturns reduce deaths due to cardiovascular causes and motor-vehicle accidents. That said, these estimates shrink in magnitude in more-disaggregated analyses, though they remain significant due to increased precision. Interestingly, only the region-level analysis indicates that economic downturns significantly increase suicides.

Table 5 presents a similar analysis but instead focuses on the effect of the economic conditions at the time of conception on the incidence of low and very low birth weights. Though the estimates are always positive, indicating that local downturns improve infant health, as in Table 4 the magnitudes of the estimated effects decline as areas are defined more narrowly.

Columns 3 through 5 address the extent to which changing economic conditions may affect the composition of newborns. In particular, Column 3 shows the estimated effect of economic conditions on the birth rate (defined as the number of births per 1,0000 women between the ages of 15 and 44). This estimate is always positive (and highly significant in more-disaggregated analyses), indicating that economic downturns reduce fertility rates.[19] That said, the estimated effects on the fraction of births to white mothers and the fraction of births to mothers under the age of 18 are usually not significant, lending support to the notion that the improvements in infant health observed during recessions are *not* due changes in the underlying composition of mothers giving birth. The county-level estimates serve as an exception, however, as they indicate that deteriorating economic conditions at the county level are associated with more births to teen mothers and fewer births to white mothers, which we would expect to reduce the incidence of low birth weight at the county level. As such, the fact that there is no significant link between county employment-to-population ratios and the incidence of low birth weight is something of a puzzle.

[18]This is a subset of the categories considered in Stevens et al. (2011). See their appendix for cause-of-death codes.

[19]Schaller (2012) also finds that fertility is procyclical.

The results discussed above clearly illustrate that the choice of geographic aggregation has a dramatic influence on the estimated relationship between economic conditions and health. In particular, more-disaggregated analyses severely understate the extent to which local downturns improve health. While simply establishing this fact is the main contribution of this paper, it naturally raises the question *why?* Given that the economic-conditions-migration gradient across socioeconomic status is similar across different definitions of areas (Section 4), two possibilities seem most likely. First, broader economic conditions may have greater impacts on health. To the extent to which the effects may be driven by individuals' *perceptions* of the economic conditions they face, this explanation is quite plausible given that individuals may view their 'local' labor market quite broadly and that broader changes in economic conditions are likely to garner more media attention. That said, lacking a valid instrument for employment-to-population ratios, we cannot rule out that this systematic pattern arises due to differences in measurement-error bias at differing levels of geographic aggregation.[20]

7 Leveraging County-Level Data for Additional Insights

In this section, I use county-level data to shed light on several questions that are difficult if not impossible to answer using the state-level data used in prior studies.

7.1 Simultaneously Estimating Effects of More- and Less-Local Economic Conditions

The fact that more-disaggregated analyses systematically yield estimates that are relatively small in magnitude raises the question: do local economic conditions matter at all or do the effects of local economic conditions simply reflect the effects of broader economic conditions? To investigate this issue, I use county-level data to separately identify the effects of county economic conditions, state economic conditions, and regional economic conditions. Because we are interested in the effect of economic conditions in an individual's own county versus the effect of economic conditions in other counties in an individual's state and region, for each

[20] There are certainly alternative measures of economic conditions that *could* be used as instruments but none seem satisfying. For example, employment counts produced by the BEA could be used to construct an alternative measure of the employment-to-population ratio. However, despite the fact that the BEA and BLS independently produce employment estimates, they largely use the same data; thus, the errors would not be independent. Moreover, as fundamentally different measures of economic conditions—BLS measures employment for county residents whereas the BEA measures the number of jobs in a county—the BEA measure may be independently related to health outcomes. Other measures of local economic conditions would appear to suffer from similar problems when considered as instruments.

observation the measure of statewide economic conditions is calculated using information from the other counties in its state and the measure of regional economic conditions is calculated using information from the other states in its region.

Table 6 shows the results of this analysis for mortality outcomes. Though these estimates continue to indicate that state and regional economic conditions are more strongly related to mortality than county economic conditions, they do reveal that county economic conditions have an independent effect on health. Similarly, these estimates indicate that state-level economic conditions affect mortality independently of the effects of regional economic conditions.

Table 7 presents a similar analysis for infant outcomes. Though the estimates corresponding to the fraction of newborns with low birth weight and very low birthweight are intriguing, potential composition bias makes interpretation difficult. That said, it is quite notable that this analysis suggests that fertility is more strongly related to the measure of regional economic conditions than to the measure of state economic conditions which is more strongly related to fertility than the measure of county economic conditions. As before, all of these estimates indicate that fertility is procyclical.

7.2 Do Local Downturns Improve Health *Everywhere* in the US?

The area approach has been used to estimate the effect of economic conditions on health in several different contexts since Ruhm (2000) and Dehejia and Lleras-Muney's (2004) analyses of the United States. In particular, local downturns have been shown to improve health using data from 16 German states (Neumayer 2004), 50 Spanish provinces (Tapia Granados 2005), 8 Asia-Pacific countries (Lin 2009), 23 OECD countries (Gerdtham and Ruhm 2006), and 21 Swedish regions (Svensson 2010).[21] With county-level data, we have the ability to separately assess the extent to which local downturns improve health for each US state.

Acknowledging that broader measures of economic conditions are more strongly related to mortality than narrow measures, Figure 2 shows state-specific estimates of the link between county employment-to-population ratios and overall mortality rates.[22] The black squares plot the estimated effects for each state and the whiskers show the associated confidence intervals. Though these state-specific estimates are often too imprecise to reject zero, a majority of the estimates are positive (31 of 47), indicating that local downturns reduce mortality for most

[21]See Ruhm (2008) for an in-depth review of many of these and other related studies. As discussed in the next section, the relationship often runs in the opposite directions for developing countries.

[22]Washington D.C. is pooled with Maryland for this analysis.

states. However, this figure illustrates that there is substantial heterogeneity and suggests that local downturns *increase* mortality in some states.

Though I present similar figures for each of the health outcomes explored in previous sections in Appendix A.1, they are usually similar to Figure 2 or too imprecise to be informative. One exception is the figure depicting state-specific estimates for the effects of local economic conditions on birth rates. These estimates are positive for a vast majority of the states considered (37 of 47) and are usually statistically significant (28 of 47), providing further evidence that fertility is procyclical. Moreover, the increases in fertility are disproportionately due do white mothers having more children, as the estimated effect on the fraction of white mothers is also positively related to employment-to-population ratios for most states.

7.3 Income and The Unemployment-Health Relationship

In this section, I conduct a meta-analysis of sorts using each of the state-specific estimates from the previous section. In particular, using each state as an observation, I consider whether state income levels can explain the extent to which mortality is procyclical. This exercise is motivated by the fact that several studies have found that economic downturns lead to poorer health in developing countries despite a wide body of evidence that downturns improve health in developed countries like the United States.[23] As such, we might expect the improvements in health associated with recessions to be especially large in high-income states.

To investigate this hypothesis, Figure 3 plots the estimated effect of county employment-to-population ratios on mortality for each state against its median income (based on the 1990 Census). Perhaps in contrast to expectations, this figure reveals a clear negative relationship (p-value=0.006). That is, it indicates that local downturns improve health most in relatively-disadvantaged states. Of course, it should be noted that this correlation is based on a relatively small sample. That said, Figure 4 shows that the same pattern is evident for *all* of the health outcomes considered in this paper.

Figures exploring the extent to which other measures of economic development predict the effect of county economic conditions on health outcomes are—shown in Appendix A.2—largely tell the same story. In particular, local downturns appear to improve health most in states with low poverty rates and a large share of college graduates. That said, the fraction of a state that

[23] For examples of studies focusing on developing countries, see Bhalotra (2010), Baird, Friedman, and Schady (2011), and Miller and Urdinola (2010).

has completed high school does not have much predictive power.

8 Conclusion

In this paper, I have demonstrated that the migratory response to fluctuations in local economic conditions are an important consideration for studies that use the area approach to estimate the effects of unemployment on health; however, because high-socioeconomic-status individuals are more likely to leave an area when its unemployment rate rises, this phenomenon will tend to result in estimates that understate the health improvements caused by recessions. I have also demonstrated that there is much to be gained by conducting more-disaggregated analyses of the effects of economic conditions on health, though the potential for measurement error to bias estimates based on measures of economic conditions for small areas must be acknowledged. With county-level data, we learn that broader measures of economic conditions are stronger predictors of mortality than county measures; that there is substantial heterogeneity in the extent to which declining county economic conditions are associated with reductions in mortality; and that local downturns improve health most in states that have relatively-disadvantaged populations. More broadly, the estimates presented in this paper suggest that recessions improve health even more than we may have thought given the existing literature.

References

ANGRIST, J., AND A. KRUEGER (1999): "Empirical Strategies in Labor Economics," in *Handbook of Labor Economics*, ed. by O. Ashenfelter, and D. Card. North Holland.

BAIRD, S., J. FRIEDMAN, AND N. SCHADY (2011): "Aggregate Income Shocks and Infant Mortality in the Developing World," *The Review of Economics and Statistics*, 93(3), 847–856.

BARTIK, T. J. (1996): "The Distributional Effects of Local Labor Demand and Industrial Mix: Estimates Using Individual Panel Data," *Journal of Urban Economics*, 40(2), 150–178.

BHALOTRA, S. (2010): "Fatal Fluctuations: Cyclicality in Infant Mortality in India," *Journal of Development Economics*, 93(1), 7–19.

BLACK, S. E., P. J. DEVEREUX, AND K. G. SALVANES (2012): "Losing Heart? The Effect of Job Displacement on Health," *NBER Working Paper*.

BLANCHARD, O. J., AND L. F. KATZ (1992): "Regional Evolutions," *Brookings Papers on Economic Activity*, 1, 1–75.

BOUND, J., AND H. J. HOLZER (2000): "Demand Shifts, Population Adjustments, and Labor Market Outcomes during the 1980s," *Journal of Labor Economics*, 18(1), 20–54.

BRENNER, M. (1973): *Mental Illness and the Economy*. Cambridge, MA: Harvard University Press.

——— (1975): "Trends in Alcohol Consumption and Associated Illnesses," *The American Journal of Public Health*, 656(12), 1279–1292.

——— (1979): "Mortality and the National Economy," *The Lancet*, 314(8142), 568–573.

CHAY, K. Y., AND M. GREENSTONE (2003): "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," *The Quarterly Journal of Economics*, 118(3), 1121–1167.

CURRIE, J., AND E. TEKIN (2011): "Is The Foreclosure Crisis Making Us Sick?," *NBER Working Paper No. 17310*.

DEHEJIA, R., AND A. LLERAS-MUNEY (2004): "Booms, Busts, and Babies' Health," *The Quarterly Journal of Economics*, 119(3), 1091–1130.

ELIASON, M., AND D. STORRIE (2009a): "Does job loss shorten life?," *Journal of Human Resources*, 44(2), 277–302.

——— (2009b): "Job loss is bad for your health–Swedish evidence on cause-specific hospitalization following involuntary job loss," *Social Science & Medicine*, 68(8), 1396–1406.

FORBES, J. F., AND A. MCGREGOR (1984): "Unemployment and Mortality in Post-War Scotland," *Journal of Health Economics*, 3(3), 239–257.

GERDTHAM, U.-G., AND M. JOHANNESSON (2005): "Business Cycles and Mortality: Results from Swedish Microdata," *Social Science and Medicine*, 60(1), 205–218.

GERDTHAM, U.-G., AND C. RUHM (2006): "Deaths Rise in Good Economic Times: Evidence from the OECD," *Economics and Human Biology*, 4(3), 298–316.

Glaeser, E. L., and J. Gyourko (2005): "Urban Decline and Durable Housing," *Journal of Political Economy*, 113(2), 345–375.

Griliches, Z. (1977): "Estimating the Returns to Schooling: Some Econometric Problems," *Econometrica*, 45(1), 1–22.

Griliches, Z., and J. Hausman (1986): "Errors in Variables in Panel Data," *Journal of Econometrics*, 33(1), 93–118.

Hausman, J. (2001): "Mismeasured Variables in Econometric Analysis: Problems from the Right and Problems from the Left," *Journal of Economic Perspectives*, 15(4), 57–67.

Hoynes, H. W. (2000): "Local Labor Markets And Welfare Spells: Do Demand Conditions Matter?," *The Review of Economics and Statistics*, 82(3), 351–368.

Johansson, E. (2004): "A Note on the Impact of Hours Worked on Mortality in OECD Countries," *The European Journal of Health Economics*, 5(4), pp. 335–340.

Johnson, K. P., and J. R. Kort (2004): "2004 Redefinition of the BEA Economic Areas," *Survey of Current Businesses*, pp. 68–75.

Joyce, T. J., and H. N. Mocan (1993): "Unemployment and Infant Health: Time-Series Evidence from the State of Tennessee," *Journal of Human Resources*, 28(1), 185–203.

Kuhn, A., R. Lalive, and J. Zweimller (2009): "The Public Health Costs of Job Loss," *Journal of Health Economics*, 28(6), 1099–1115.

Laporte, A. (2004): "Do Economic Cycles Have a Permanent Effect on Population Health? Revisiting the Brenner Hypothesis," *Health Economics*, 13(8), 767–779.

Lin, S.-J. (2009): "Economic Fluctuations and Health Outcome: A Panel Analysis of Asia-Pacific Countries," *Applied Economics*, 41(4), 519–530.

Lindo, J. M. (2011): "Parental Job Loss and Infant Health," *Journal of Health Economics*, 30(5), 869–879.

McAvinchey, I. D. (1988): "A Comparison of Unemployment, Income and Mortality Interaction for Five European Countries," *Applied Economics*, 20(4), 453–471.

Miller, D. L., M. E. Page, A. H. Stevens, and M. Filipski (2009): "Why Are Recessions Good for Your Health?," *American Economic Review*, 99(2), 122–127.

Miller, G., and P. Urdinola (2010): "Cyclicality, Mortality, and the Value of Time: The Case of Coffee Price Fluctuations and Child Survival in Colombia," *Journal of Political Economy*, 118(1), 113–155.

Neumayer, E. (2004): "Recessions Lower (Some) Mortality Rates," *Social Science and Medicine*, 58(6), 1037–1047.

Notowidigdo, M. J. (2011): "The Incidence of Local Labor Demand Shocks," NBER Working Papers 17167, National Bureau of Economic Research, Inc.

Ruhm, C. J. (2000): "Are Recessions Good For Your Health?," *The Quarterly Journal of Economics*, 115(2), 617–650.

——— (2003): "Good times make you sick," *Journal of Health Economics*, 22(4), 637–658.

——— (2005): "Healthy living in hard times," *Journal of Health Economics*, 24(2), 341–363.

——— (2007): “A Healthy Economy Can Break Your Heart,” *Demography*, 44(4), 829–848.

——— (2008): “Macroeconomic Conditions, Health and Government Policy,” in *Making Americans Healthier: Social and Economic Policy as Health Policy: Rethinking Americas Approach to Improving Health*, ed. by R. F. Schoeni, J. S. House, G. A. Kaplan, and H. Pollack. New York: Russell Sage Foundation.

Saks, R. E., and A. Wozniak (2011): “Labor Reallocation over the Business Cycle: New Evidence from Internal Migration,” *Journal of Labor Economics*, 29(4), 697 – 739.

Schaller, J. (2012): “Boom, Busts, and Fertility: Testing the Becker Model Using Gender-Specific Labor Demand,” *University of Arizona Working Paper*.

Stevens, A. H., D. L. Miller, M. E. Page, and M. Filipski (2011): “The Best of Times, the Worst of Times: Understanding Pro-cyclical Mortality,” *NBER Working Paper No. 17657*.

Sullivan, D., and T. von Wachter (2009): “Job Displacement and Mortality: An Analysis Using Administrative Data,” *The Quarterly Journal of Economics*, 124(3), 1265–1306.

Svensson, M. (2007): “Do not go breaking your heart: Do economic upturns really increase heart attack mortality?,” *Social Science & Medicine*, 65(4), 833–841.

Tapia Granados, J. (2005): “Recessions and Mortality in Spain, 1980-1997,” *European Journal of Population*, 21(4), 393–422.

Wozniak, A. (2010): “Are College Graduates More Responsive to Distant Labor Market Opportunities?,” *Journal of Human Resources*, 45(4), 944–970.

Figure 1
Mapping of Counties to BEA Economic Areas

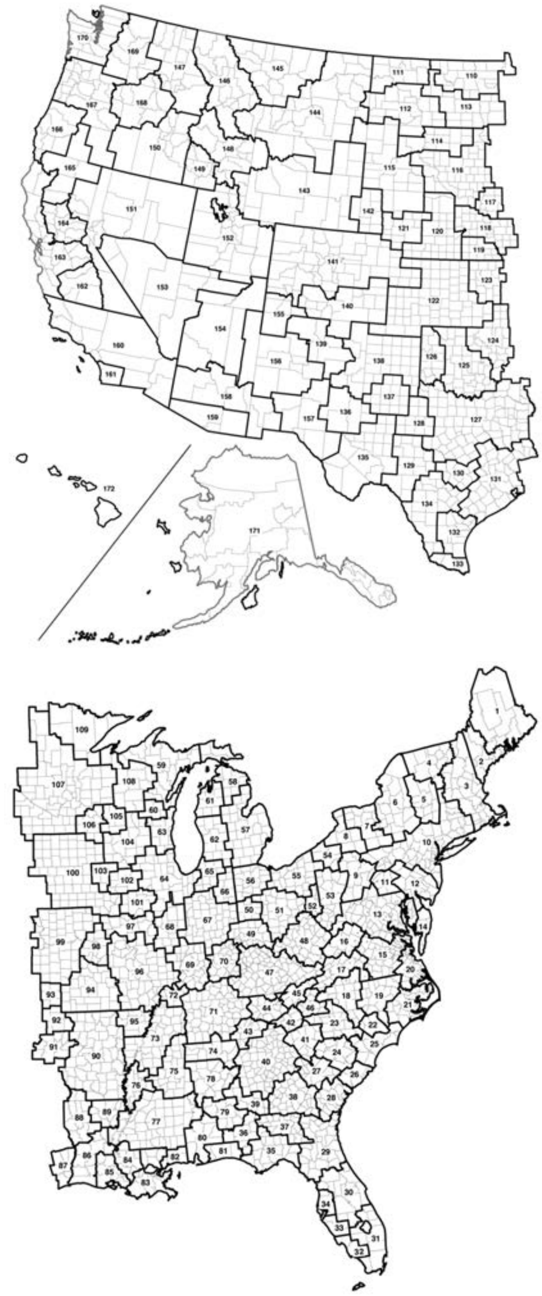
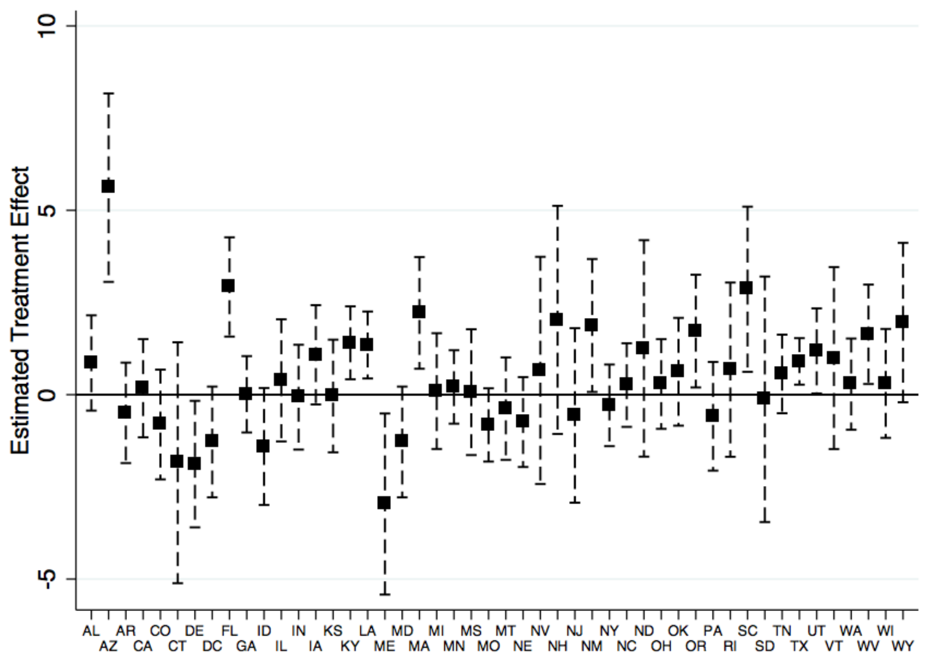
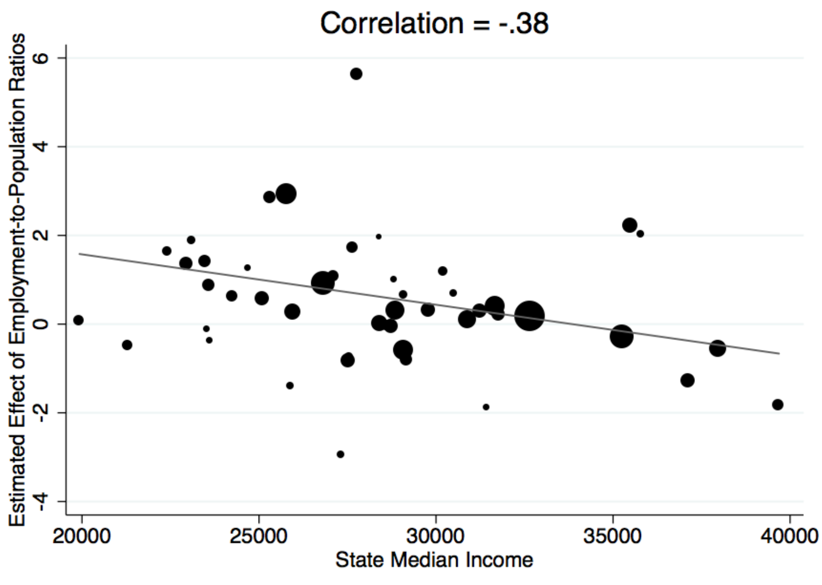


Figure 2
State-Specific Estimates of The Effect of County Economic Conditions on Overall Mortality



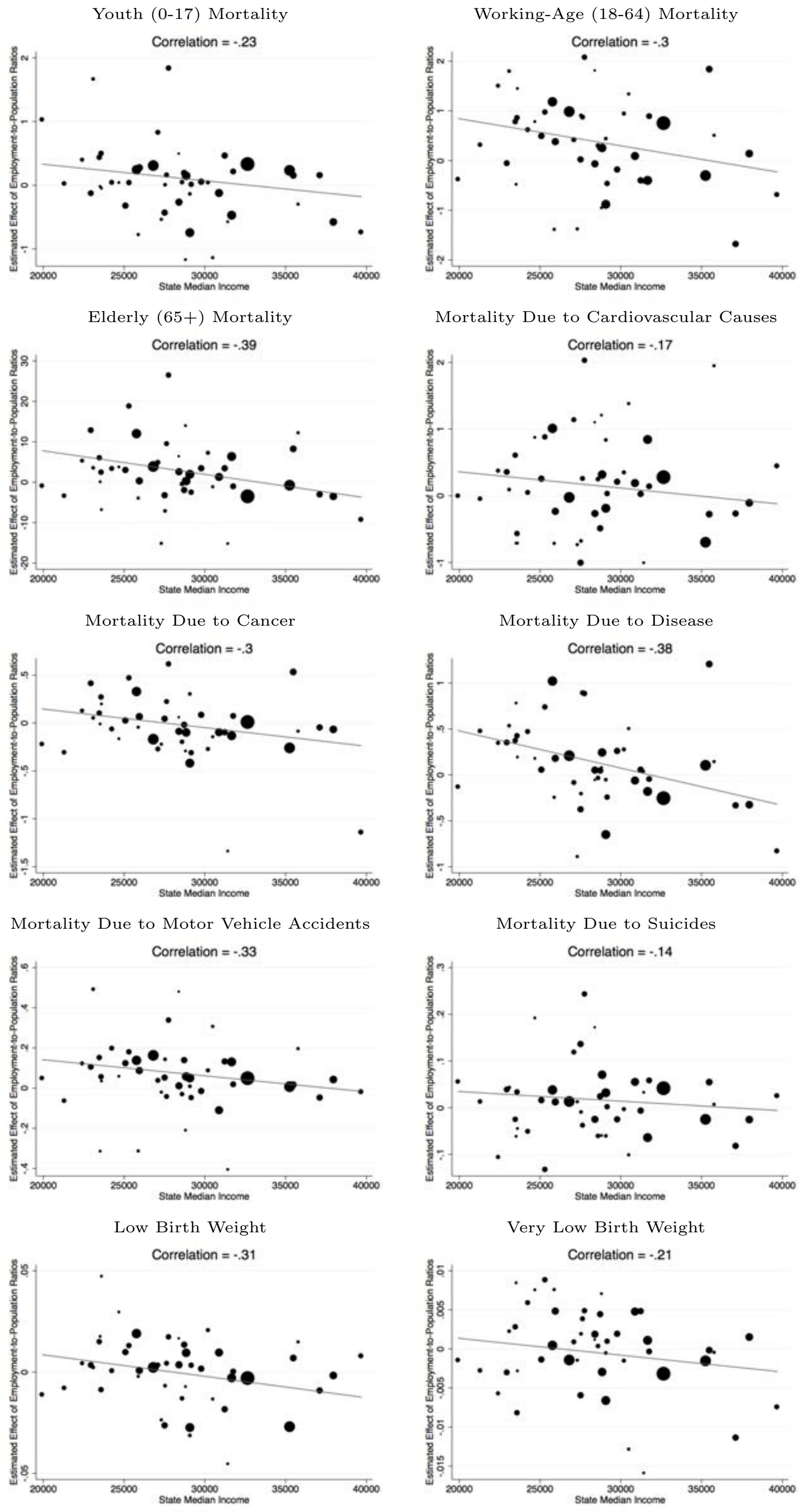
Notes: Each black square represents the estimated effect of local economic conditions—as measured by county employment-to-population ratios—on overall mortality for a given state, while the whiskers represent the associated 95-percent confidence intervals. These estimates are based on county-level data spanning 1976 to 2007, control for year fixed effects, county fixed effects, county-specific trends, and demographic characteristics while weighting estimates by the county population and clustering standard-error estimates at the county level. See Section 7.2 for further information. County-level data is based on employment counts produced by the BLS, population data produced by SEER, and death counts from restricted-use Vital Statistics' micro-record multiple-cause-of-death files provided by the NCHS.

Figure 3
State Median Incomes and The Effects of County Economic Conditions on Overall Mortality



Notes: Each observation represents a state. Its horizontal position is its median income (based on the 1990 Census) and its vertical position is the estimated effect of county employment-to-population ratios on its overall mortality rate. The size of each observation is proportional to the size of the population that it represents over the sample period. The reported correlation uses population weights. For additional notes on the state-specific estimates, see Figure 2.

Figure 4
State Median Incomes and The Effects of County Economic Conditions on Other Health Outcomes



Notes: Each observation represents a state. Its horizontal position is its median income (based on the 1990 census) and its vertical position is the estimated effect of county employment-to-population ratios on mortality (or employment-to-population ratios at the time of conception on the incidence of low birth weight). The size of each observation is proportional to the size of the population that it represents over the sample period. Reported correlations also use population weights. For additional notes on the state-specific estimates, see Figure 2.

Table 1
Estimated Effects of Economic Conditions on Moving Areas Using PSID Data

	(1)	(2)	(3)
Panel A: Region-Level Estimates (8 Areas)			
Employment-to-Population Ratio	0.00235***	0.00359***	0.00300***
	(0.00086)	(0.00084)	(0.00090)
(Employment-to-Population Ratio)*(High School Graduate)		-0.00152***	
		(0.00035)	
(Employment-to-Population Ratio)*(Perm. Income Decile)			-0.00011
			(0.00007)
Observations	193849	193849	193849
Individuals	16901	16901	16901
Panel B: State-Level Estimates (48 Areas)			
Employment-to-Population Ratio	-0.00148**	0.00042	0.00008
	(0.00065)	(0.00071)	(0.00080)
(Employment-to-Population Ratio)*(High School Graduate)		-0.00228***	
		(0.00049)	
(Employment-to-Population Ratio)*(Perm. Income Decile)			-0.00026***
			(0.00008)
Observations	193849	193849	193849
Individuals	16901	16901	16901
Panel C: BEA-Economic-Area-Level Estimates (176 Areas)			
Employment-to-Population Ratio	-0.00087*	0.00062	0.00018
	(0.00045)	(0.00053)	(0.00064)
(Employment-to-Population Ratio)*(High School Graduate)		-0.00185***	
		(0.00047)	
(Employment-to-Population Ratio)*(Perm. Income Decile)			-0.00018**
			(0.00008)
Observations	193849	193849	193849
Individuals	16901	16901	16901
Panel D: BEA-Component-Economic-Area-Level Estimates (334 Areas)			
Employment-to-Population Ratio	-0.00174***	-0.00016	-0.00080
	(0.00045)	(0.00055)	(0.00067)
(Employment-to-Population Ratio)*(High School Graduate)		-0.00194***	
		(0.00051)	
(Employment-to-Population Ratio)*(Perm. Income Decile)			-0.00016*
			(0.00009)
Observations	193849	193849	193849
Individuals	16901	16901	16901
Panel E: County-Level Estimates (2938 Areas)			
Employment-to-Population Ratio	-0.00067***	0.00027	0.00047
	(0.00025)	(0.00041)	(0.00047)
(Employment-to-Population Ratio)*(High School Graduate)		-0.00116**	
		(0.00047)	
(Employment-to-Population Ratio)*(Perm. Income Decile)			-0.00020***
			(0.00007)
Observations	193849	193849	193849
Individuals	16901	16901	16901

Notes: Estimates are based on the 1976–1997 waves of the PSID. For each year, the sample is restricted to individuals at least 24 years old who are not a part of the PSID's special "Latino Sample." All estimates are based on models with individual fixed effects and year fixed effects. Panel A uses an indicator for moving to a new BEA region as the outcome variable and the employment-to-population ratio in an individual's region as the regressor. Panels B uses an indicator for moving to a new state as the outcome variable and the employment-to-population ratio in an individual's state as the regressor. Panels C through E are similar but consider more-narrow definitions of area. See the text for the construction of the measure of permanent income.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2
State-level Estimates of the Effects of Economic Conditions on Overall Mortality (Per 100,000 Residents)

	Prior Estimates		New Estimates						
	Ruhm (2000)	Stevens et al. (2011)	Using BLS Unemployment Data	Using Controls Available For Counties	Adding Earlier Years	Adding Later Year	Using County Matched Data	Not Taking Log of Mortality Rate	Alt. Measure of Economic Conditions
Years Analyzed:	1972-1991	1978-2006	1978-2006	1978-2006	1976-2006	1976-2007	1976-2007	1976-2007	1976-2007
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Unemployment Rate	-0.0054***	-0.0033***	-0.0033***	-0.0033***	-0.0044***	-0.0042***	-0.0043***	-4.0087***	
	(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0011)	(0.0011)	(0.8642)	
Employment-tp-Population Ratio									3.2350***
									(0.8423)
Observations	930	1479	1479	1479	1581	1632	1509	1509	1509
Semi-Elasticity	-0.0054	-0.0033	-0.0033	-0.0033	-0.0044	-0.0042	-0.0043	-0.0047	0.0038

Notes: See Section 5.1 for details on the data and measures used in each column. All regressions include year fixed effects, state fixed effects, and state-specific trends. In addition, all regressions are weighted by the population counts in each cell and cluster standard-error estimates on the state.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3
State-level Estimates of the Effect of Economic Conditions at the Time of Conception on Birth Weights

	Dehejia & Lleras-Muney (2004)	Impute Conception Year	Including All Races	Including All Ages of Mothers	Collapsing Race-Level Data	Adding Mother Age Controls	Adding Recent Years	Using County Matched Data	Alt. Measure of Economic Conditions
Years Analyzed:	1976-1999	1976-1999	1976-1999	1976-1999	1976-1999	1976-1999	1976-2006	1976-2006	1976-2006
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome: Fraction With Low Birthweight									
Unemployment Rate	-0.0180***	-0.0171*	-0.0167**	-0.0157*	-0.0144*	-0.0177**	-0.0282***	-0.0287***	
	(0.0063)	(0.0088)	(0.0080)	(0.0079)	(0.0072)	(0.0072)	(0.0070)	(0.0074)	
Employment-to-Population Ratio									0.0255***
									(0.0081)
Observations	2447	2448	3672	3672	1224	1224	1581	1461	1461
Semi-Elasticity	-0.2600	-0.0025	-0.0024	-0.0022	-0.0020	-0.0025	-0.0039	-0.0039	0.0035
Outcome: Fraction With Very-Low Birthweight									
Unemployment Rate	-0.0066*	-0.0047*	-0.0047**	-0.0050**	-0.0047**	-0.0039*	-0.0065***	-0.0061***	
	(0.0035)	(0.0025)	(0.0023)	(0.0021)	(0.0021)	(0.0023)	(0.0023)	(0.0023)	
Employment-to-Population Ratio									0.0061**
									(0.0028)
Observations	2447	2448	3672	3672	1224	1224	1581	1461	1461
Semi-Elasticity	-0.5400	-0.0038	-0.0039	-0.0039	-0.0037	-0.0031	-0.0049	-0.0046	0.0046

Notes: See section 5.2 for details on the data and measures used in each column. All regressions include year fixed effects, state fixed effects, and state-specific trends. In addition, all regressions are weighted by the number of births in each cell and cluster standard-error estimates on the state.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4
Estimated Effects of Economic Conditions on Mortality (Per 100,000 Residents)

Age:	All	0-17	18-64	65+	All	All	All	All	All
Cause:	All	All	All	All	Cardio	Cancer	Disease†	Vehicle	Suicide
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: Region-Level Estimates (8 Areas)									
Employment-to-Population Ratio	4.3127**	1.6663**	1.4939	19.2719**	2.5835**	-0.5189	0.4992	0.6183***	-0.2162**
	(1.6595)	(0.4792)	(1.2125)	(6.9092)	(0.8817)	(0.2968)	(0.7767)	(0.1593)	(0.0769)
Observations	253	253	253	253	253	253	253	253	253
Semi-Elasticity	0.0051	0.0182	0.0044	0.0040	0.0071	-0.0027	0.0037	0.0347	-0.0185
Panel B: State-Level Estimates (48 Areas)									
Employment-to-Population Ratio	3.2350***	0.9188***	1.4946**	13.8255***	1.6004***	-0.2210	0.4444	0.3717***	-0.0123
	(0.8423)	(0.2773)	(0.6816)	(3.9632)	(0.5533)	(0.1944)	(0.3631)	(0.0802)	(0.0477)
Observations	1509	1509	1509	1509	1509	1509	1509	1509	1509
Semi-Elasticity	0.0038	0.0100	0.0044	0.0028	0.0044	-0.0011	0.0033	0.0209	-0.0011
Panel C: BEA-Economic-Area-Level Estimates (176 Areas)									
Employment-to-Population Ratio	2.6465***	0.7705***	1.4950***	11.2612***	1.0961***	0.0152	0.4115*	0.3064***	-0.0355
	(0.4942)	(0.1773)	(0.3759)	(2.4185)	(0.2807)	(0.1351)	(0.2371)	(0.0548)	(0.0417)
Observations	5521	5521	5521	5521	5521	5521	5521	5521	5521
Semi-Elasticity	0.0031	0.0084	0.0044	0.0023	0.0030	0.0001	0.0031	0.0172	-0.0030
Panel D: BEA-Component-Economic-Area-Level Estimates (334 Areas)									
Employment-to-Population Ratio	2.4353***	0.6397***	1.3991***	10.5333***	0.9729***	0.0702	0.3922*	0.2764***	-0.0174
	(0.4003)	(0.1378)	(0.2916)	(1.9369)	(0.2176)	(0.1125)	(0.2007)	(0.0441)	(0.0350)
Observations	10515	10515	10515	10515	10515	10515	10515	10515	10515
Semi-Elasticity	0.0029	0.0070	0.0041	0.0022	0.0027	0.0004	0.0029	0.0155	-0.0015
Panel E: County-Level Estimates (2938 Areas)									
Employment-to-Population Ratio	0.7280***	0.1735**	0.4372***	3.5651***	0.2398**	-0.0306	0.0957	0.0978***	0.0085
	(0.1888)	(0.0657)	(0.1387)	(1.0031)	(0.0915)	(0.0471)	(0.0583)	(0.0205)	(0.0098)
Observations	91754	91754	91754	91754	91754	91754	91754	91754	91754
Semi-Elasticity	0.0009	0.0019	0.0013	0.0007	0.0007	-0.0002	0.0007	0.0055	0.0007

Notes: Data aggregated to the area level, spanning 1976–2007, are based on labor force data produced by the BLS, population data produced by SEER, and death counts from restricted-use Vital Statistics' micro-record multiple-cause-of-death files provided by the NCHS. All estimates control for year fixed effects, area fixed effects, area-specific trends, and demographics, and are weighted by the population in each cell. Standard-error estimates, shown in parentheses, are clustered on the area defined by the level of geographic aggregation, except for the county-level analyses where standard-error estimates are more conservative when clustered at the state level.
†Disease category includes deaths involving respiratory problems, infections and immune deficiencies, degenerative brain diseases, and kidney problems.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5

Estimated Effects of of Economic Conditions on at the Time of Conception on Infant Outcomes

	Health at Birth		Selection		
	Fraction With Low Birthweight (1)	Fraction With Very-Low Birthweight (2)	Birth Rate (3)	Fraction With White Mother (4)	Fraction With Mother Age<18 (5)
Panel A: Region-Level Estimates (8 Areas)					
Employment-to-Population Ratio	0.0258	0.0115*	0.1932	-0.1214	0.0357
	(0.0168)	(0.0054)	(0.1257)	(0.0931)	(0.0570)
Observations	245	245	245	245	245
Semi-Elasticity	0.0035	0.0087	0.0126	-0.0015	0.0076
Panel B: State-Level Estimates (48 Areas)					
Employment-to-Population Ratio	0.0255***	0.0061**	0.1662*	-0.0021	0.0021
	(0.0081)	(0.0028)	(0.0869)	(0.0736)	(0.0226)
Observations	1461	1461	1461	1461	1461
Semi-Elasticity	0.0035	0.0046	0.0108	-0.0000	0.0004
Panel C: BEA-Economic-Area-Level Estimates (176 Areas)					
Employment-to-Population Ratio	0.0220***	0.0041**	0.1503**	0.0160	-0.0070
	(0.0052)	(0.0019)	(0.0614)	(0.0391)	(0.0150)
Observations	5345	5345	5345	5345	5345
Semi-Elasticity	0.0030	0.0031	0.0097	0.0002	-0.0015
Panel D: BEA-Component-Economic-Area-Level Estimates (334 Areas)					
Employment-to-Population Ratio	0.0180***	0.0039**	0.1474***	0.0394	-0.0089
	(0.0043)	(0.0016)	(0.0460)	(0.0325)	(0.0120)
Observations	10179	10179	10179	10179	10179
Semi-Elasticity	0.0024	0.0029	0.0095	0.0005	-0.0019
Panel E: County-Level Estimates (2938 Areas)					
Employment-to-Population Ratio	0.0018	0.0001	0.0672***	0.0618***	-0.0111***
	(0.0025)	(0.0006)	(0.0216)	(0.0119)	(0.0036)
Observations	88815	88815	88815	88815	88815
Semi-Elasticity	0.0002	0.0000	0.0043	0.0008	-0.0024

Notes: Data aggregated to the area level, spanning 1976–2006, are based on labor force data produced by the BLS, population data produced by SEER, and birth information from restricted-use natality files provided by the NCHS. All estimates control for year fixed effects, area fixed effects, area-specific trends, and demographics (with the exception of columns 3–5 which do not control for demographics), and are weighted by the population in each cell. Standard error estimates, shown in parentheses, are clustered on the area defined by the level of geographic aggregation, except for the county-level analyses where standard-error estimates are more conservative clustered at the state level.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6

Estimated Effects of Economic Conditions on Mortality (Per 100,000 Residents)

Age:	All	0-17	18-64	65+	All	All	All	All	All
Cause:	All	All	All	All	Cardio	Cancer	Disease†	Vehicle	Suicide
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: County-Level Estimates (2938 Areas)									
County Employment-to-Population Ratio	0.5686***	0.1117	0.3612**	2.8539***	0.1795**	-0.0439	0.0919	0.0776***	0.0094
	(0.1842)	(0.0667)	(0.1503)	(0.9601)	(0.0865)	(0.0429)	(0.0631)	(0.0215)	(0.0086)
State Employment-to-Population Ratio	2.9883***	1.0434***	1.6785**	12.0581***	1.0132**	0.2982	0.1937	0.3503***	-0.0170
	(0.7446)	(0.2683)	(0.7184)	(3.0288)	(0.4475)	(0.1965)	(0.3469)	(0.0562)	(0.0422)
Observations	91722	91722	91722	91722	91722	91722	91722	91722	91722
County-Semi-Elasticity	0.0007	0.0012	0.0011	0.0006	0.0005	-0.0002	0.0007	0.0044	0.0008
State-Semi-Elasticity	0.0035	0.0114	0.0049	0.0025	0.0028	0.0015	0.0014	0.0196	-0.0015
Panel B: County-Level Estimates (2938 Areas)									
County Employment-to-Population Ratio	0.5450***	0.1046	0.3557**	2.7240***	0.1626*	-0.0391	0.0874	0.0753***	0.0115
	(0.1906)	(0.0667)	(0.1533)	(0.9917)	(0.0877)	(0.0424)	(0.0653)	(0.0213)	(0.0085)
State Employment-to-Population Ratio	2.5700***	0.9075***	1.5832**	9.7952***	0.7129*	0.3831*	0.1130	0.3097***	0.0198
	(0.6963)	(0.2707)	(0.6846)	(2.8077)	(0.4235)	(0.2122)	(0.3859)	(0.0655)	(0.0364)
Regional Employment-to-Population Ratio	2.3766**	0.7517*	0.5427	13.5654***	1.7062**	-0.4823	0.4587	0.2308*	-0.2092***
	(0.9292)	(0.3877)	(0.9594)	(3.6117)	(0.7111)	(0.3427)	(0.6267)	(0.1191)	(0.0598)
Observations	91722	91722	91722	91722	91722	91722	91722	91722	91722
County-Semi-Elasticity	0.0006	0.0011	0.0010	0.0006	0.0004	-0.0002	0.0006	0.0042	0.0010
State-Semi-Elasticity	0.0030	0.0099	0.0046	0.0020	0.0019	0.0020	0.0008	0.0174	0.0017
Region-Semi-Elasticity	0.0028	0.0082	0.0016	0.0028	0.0046	-0.0025	0.0034	0.0129	-0.0179

Notes: See Table 4.
†Disease category includes deaths involving respiratory problems, infections and immune deficiencies, degenerative brain diseases, and kidney problems.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7
Estimated Effects of of Economic Conditions on at the Time of Conception on Infant Outcomes

	Health at Birth		Selection		
	Fraction With Low Birthweight (1)	Fraction With Very-Low Birthweight (2)	Birth Rate (3)	Fraction With White Mother (4)	Fraction With Mother Age<18 (5)
Panel A: County-Level Estimates (2938 Areas)					
County Employment-to-Population Ratio	-0.0011	-0.0009	0.0521***	0.0718***	-0.0122***
	(0.0026)	(0.0007)	(0.0192)	(0.0115)	(0.0029)
State Employment-to-Population Ratio	0.0298***	0.0101***	0.1624***	-0.1092*	0.0105
	(0.0102)	(0.0029)	(0.0568)	(0.0571)	(0.0197)
Observations	88784	88784	88784	88784	88784
County-Semi-Elasticity	-0.0001	-0.0006	0.0033	0.0009	-0.0026
State-Semi-Elasticity	0.0041	0.0076	0.0104	-0.0014	0.0022
Panel B: County-Level Estimates (2938 Areas)					
County Employment-to-Population Ratio	-0.0008	-0.0008	0.0498**	0.0717***	-0.0127***
	(0.0026)	(0.0007)	(0.0191)	(0.0116)	(0.0028)
State Employment-to-Population Ratio	0.0341***	0.0104***	0.1134*	-0.1120*	-0.0013
	(0.0109)	(0.0029)	(0.0594)	(0.0648)	(0.0175)
Regional Employment-to-Population Ratio	-0.0250	-0.0020	0.2791**	0.0159	0.0675**
	(0.0179)	(0.0047)	(0.1102)	(0.0960)	(0.0311)
Observations	88784	88784	88784	88784	88784
County-Semi-Elasticity	0.3126	-7.7432	0.5966	-21.4762	2.0283
State-Semi-Elasticity	-12.5968	96.5321	1.3567	33.5348	0.2131
Region-Semi-Elasticity	9.2450	-18.4505	3.3407	-4.7523	-10.7569

Notes: See Table 5.
* significant at 10%; ** significant at 5%; *** significant at 1%

Appendix A.1

Additional State-Specific Estimates

NOT INTENDED FOR PUBLICATION

Notes for all tables in Appendix A.1: Each black square represents the estimated effect of county employment-to-population ratios on the outcome for a given state while the whiskers represent the associated 95-percent confidence intervals. These estimates are based on county-level data, control for year fixed effects, county fixed effects, county-specific trends, and demographic characteristics while weighting estimates by the relevant population and clustering standard-error estimates at the county level.

Figure A1
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on Age 0-17 Mortality

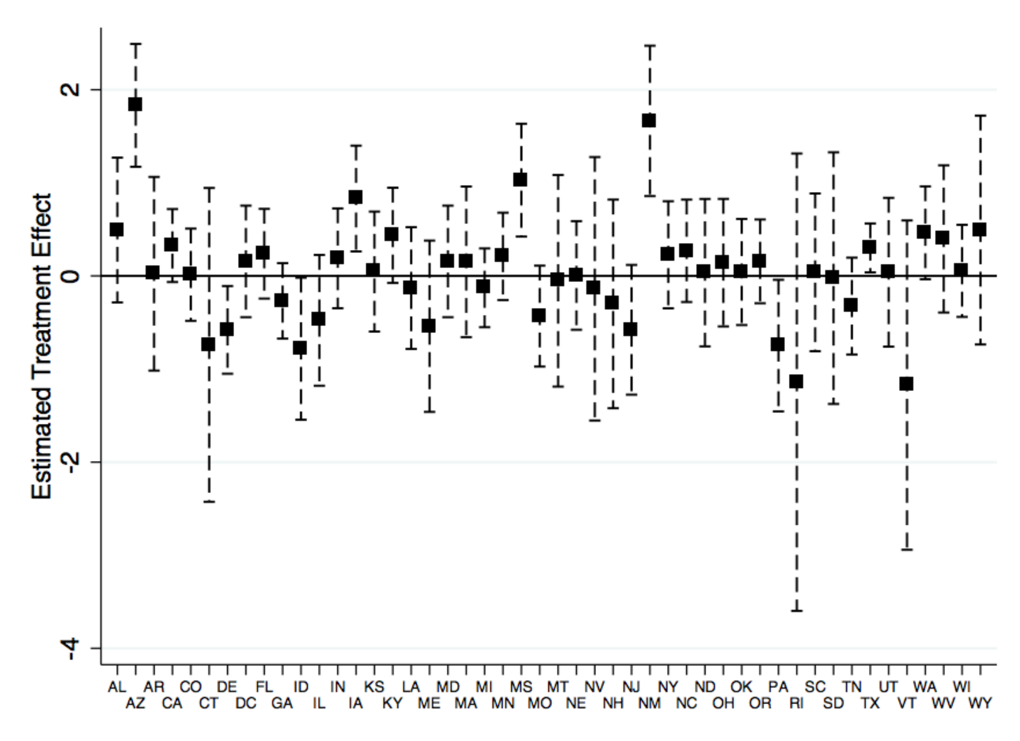


Figure A2
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on Age 18-64 Mortality

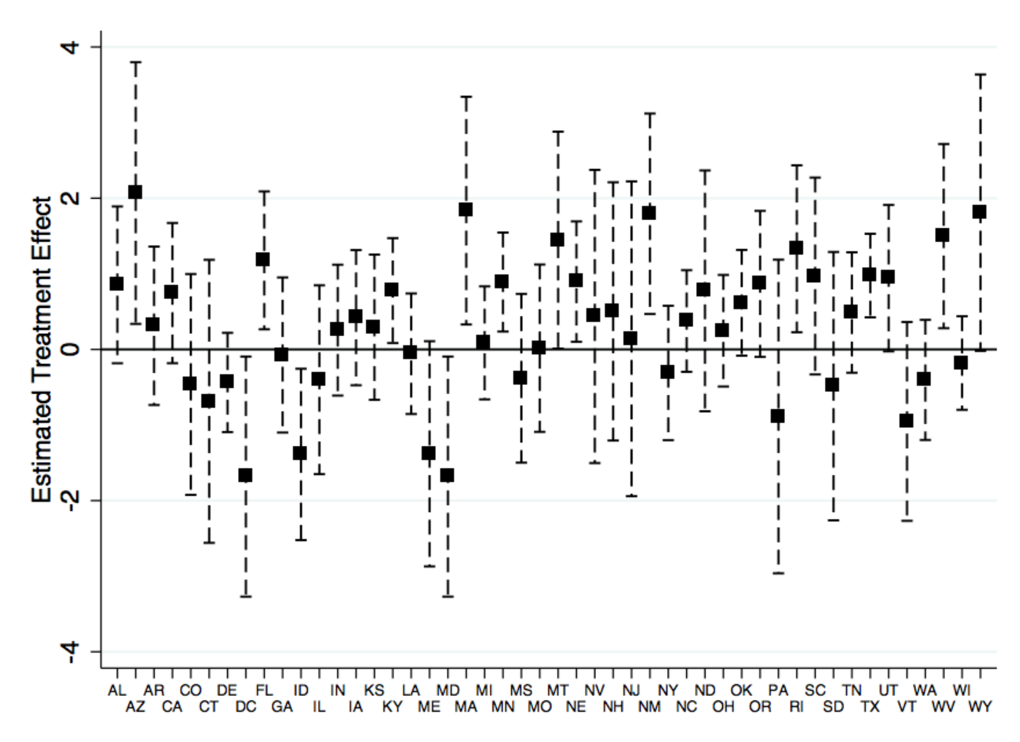


Figure A3
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on Age 65+ Mortality

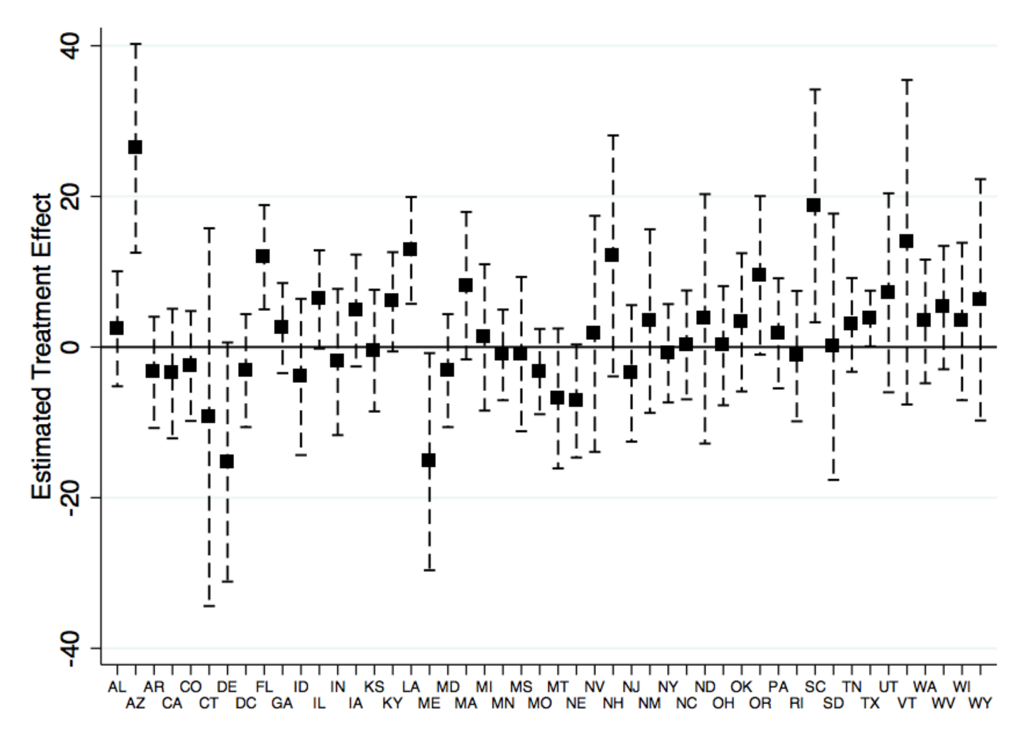


Figure A4
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on Mortality Due to Cardiovascular Causes

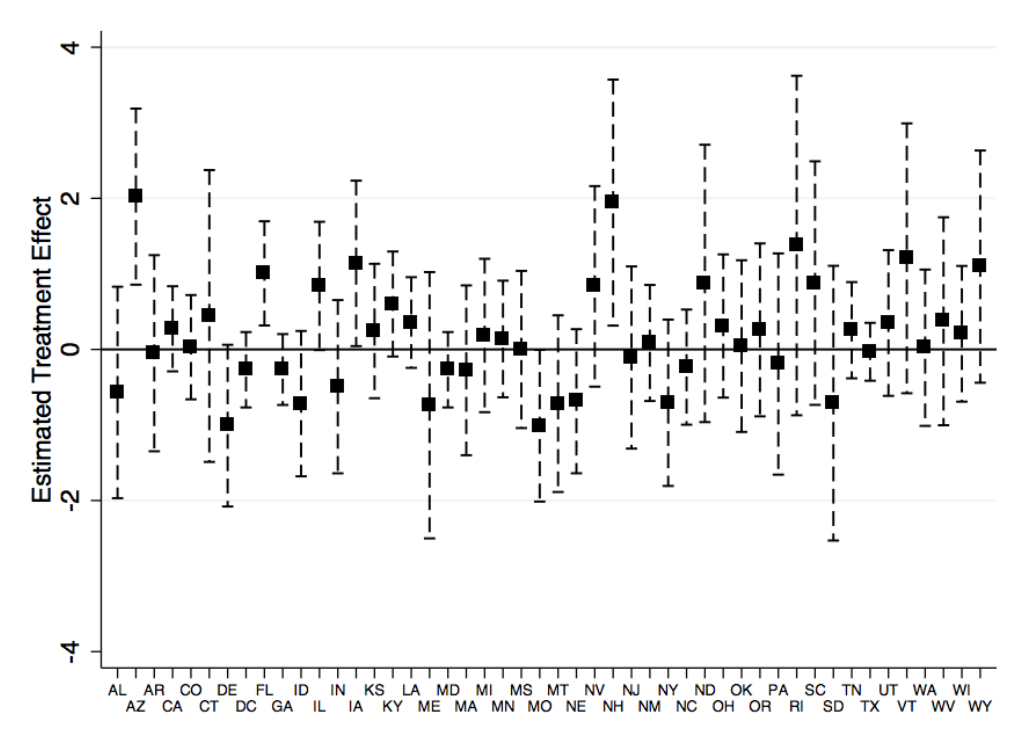


Figure A5
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on Mortality Due to Cancer

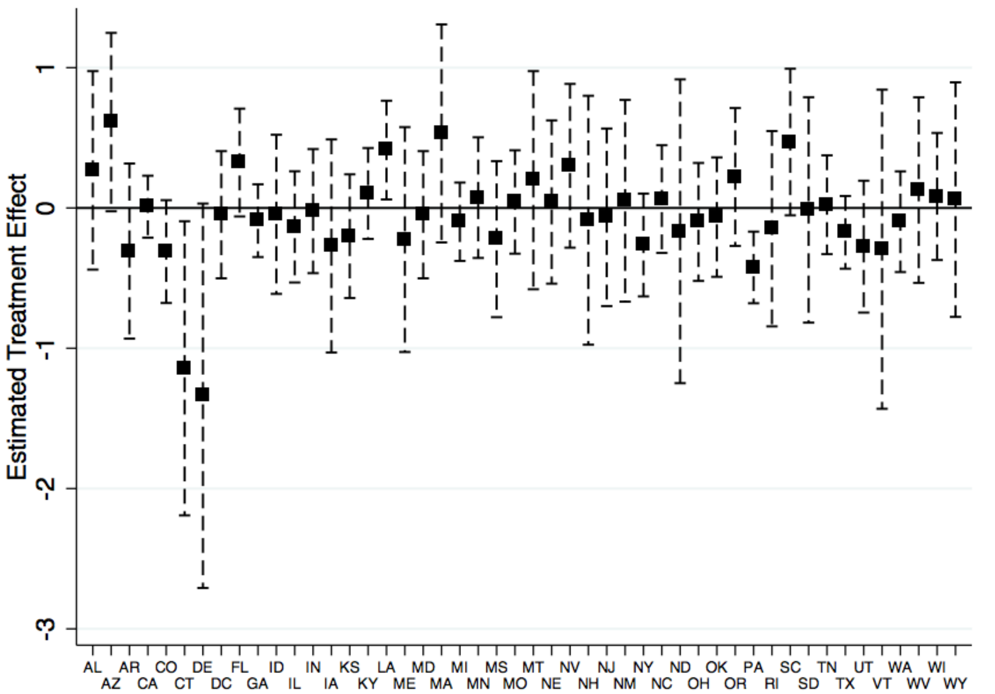


Figure A6
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on Mortality Due to Disease

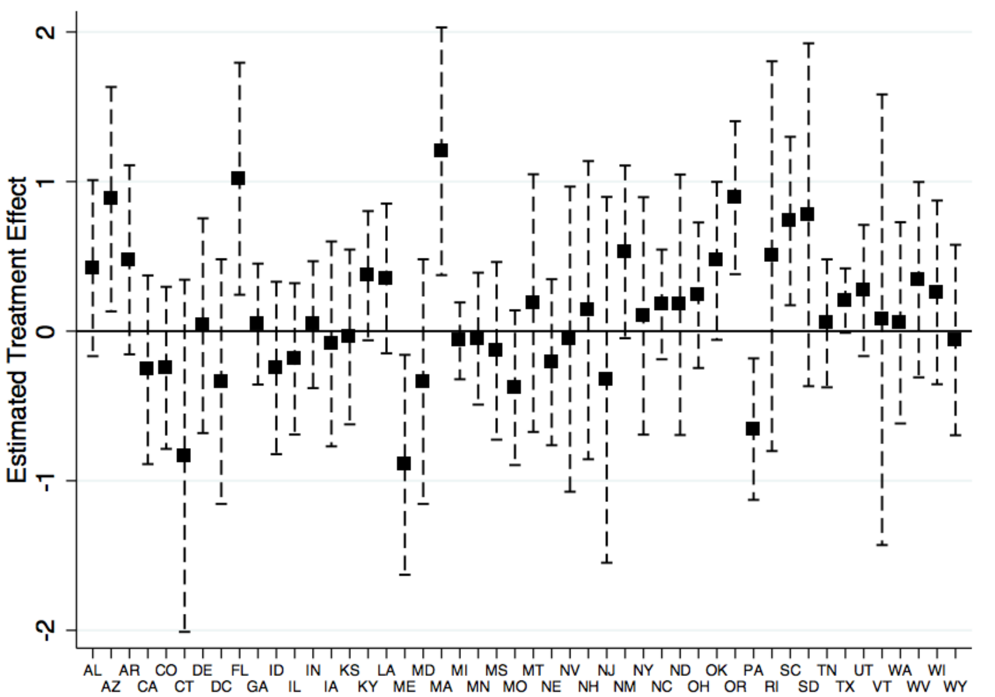


Figure A7
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on Mortality Due to Motor Vehicle Accidents

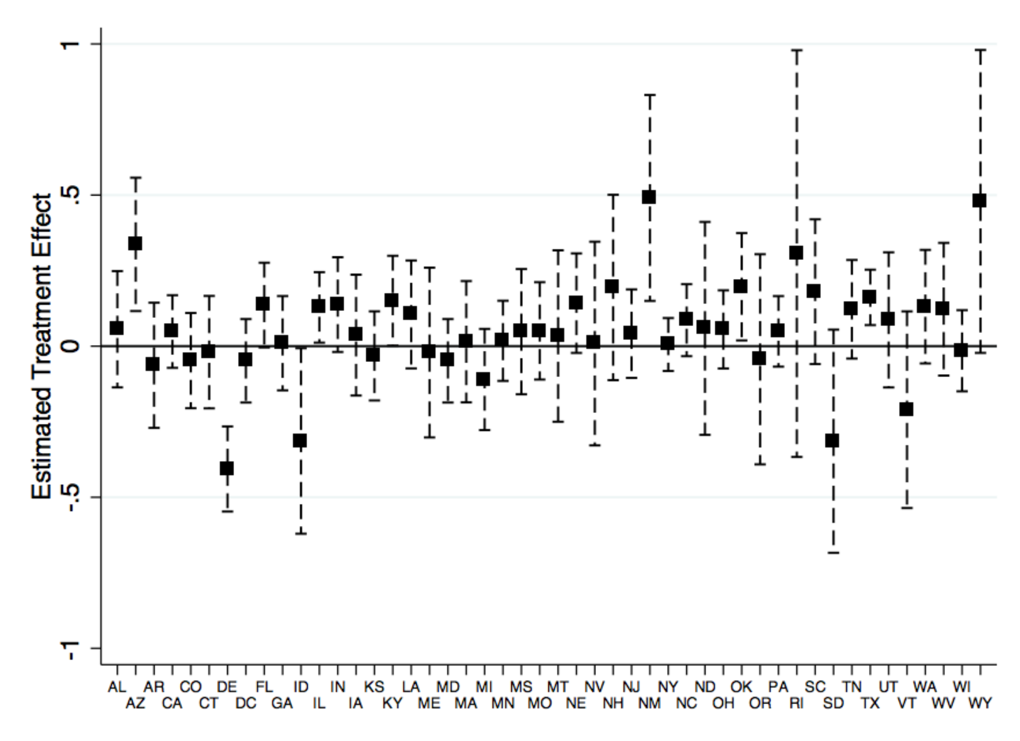


Figure A8
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on Mortality Due to Suicide

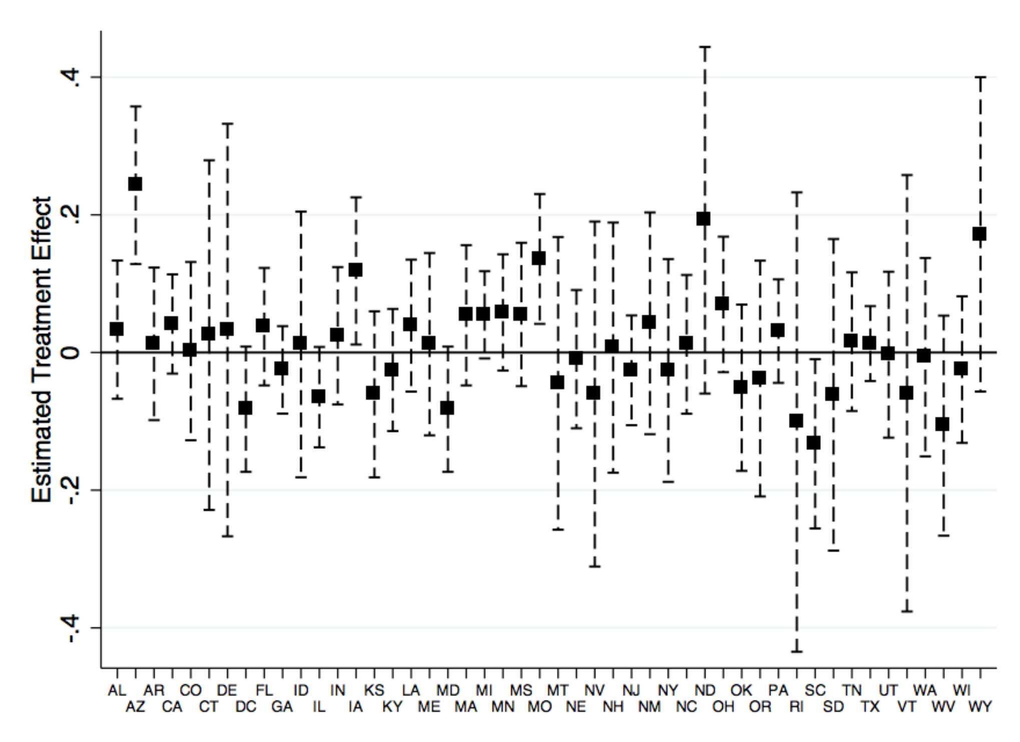


Figure A9
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on the Fraction of Births with Low Birth Weight

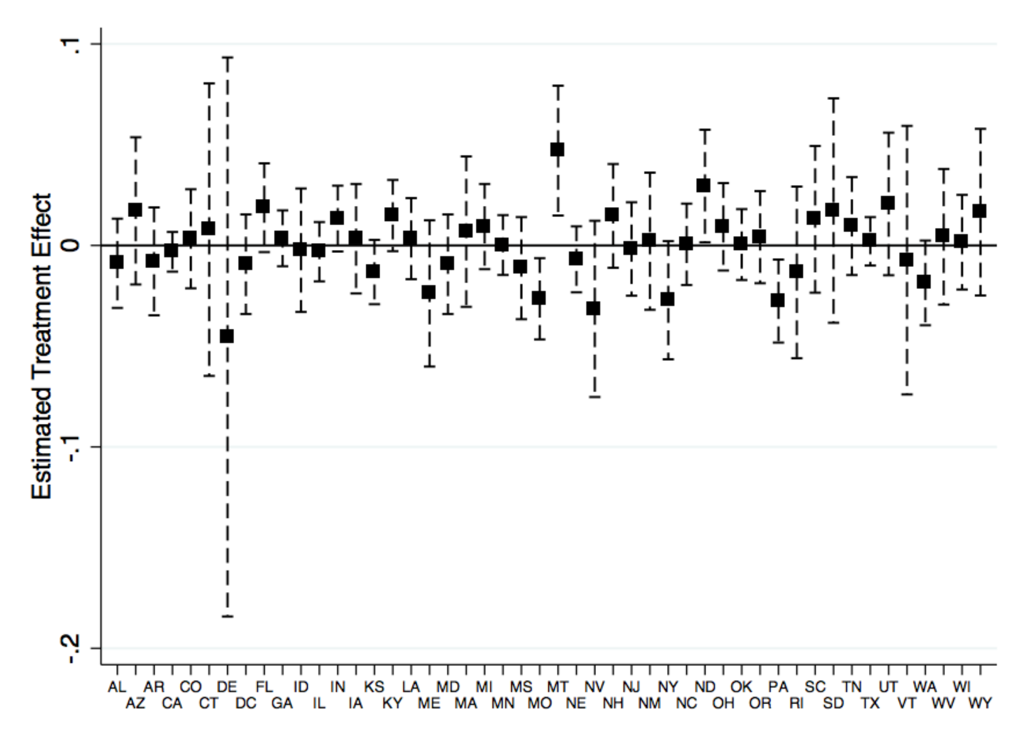


Figure A10
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on the Fraction of Births with Very-Low Birth Weight

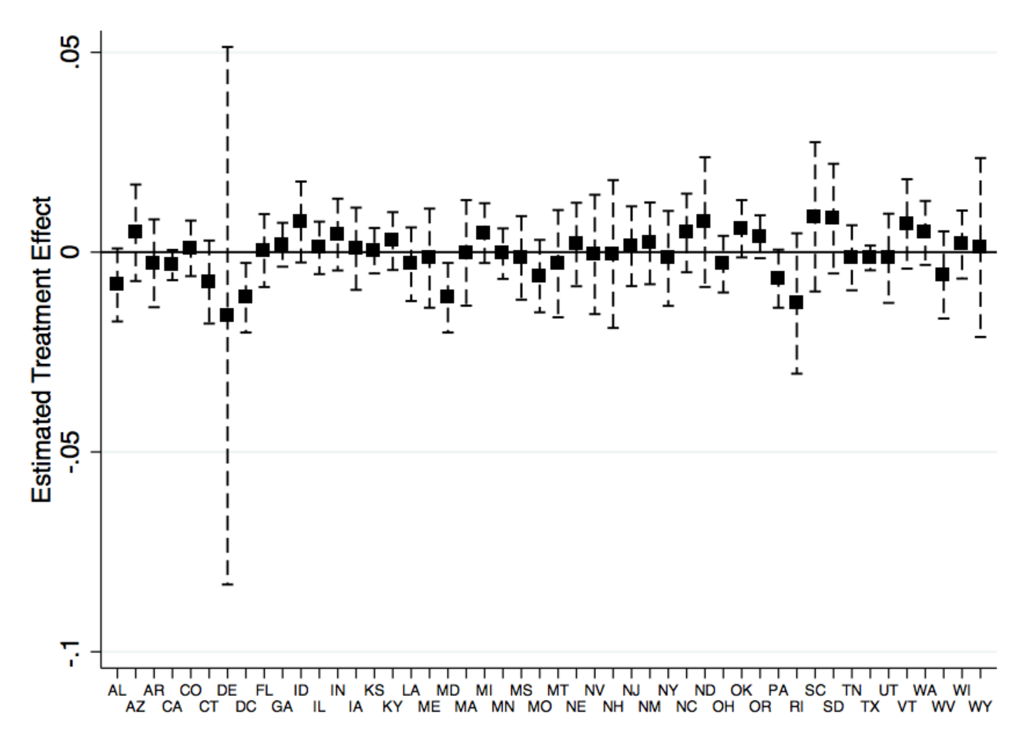


Figure A11
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on Birth Rate

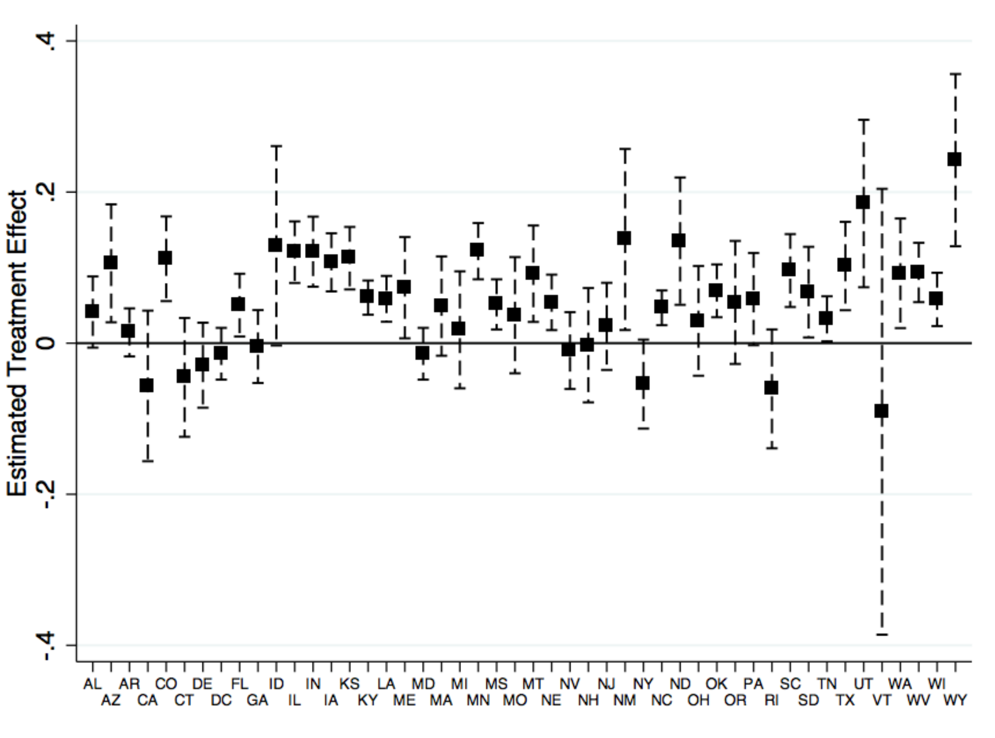


Figure A12
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on the Fraction of Births to White Mothers

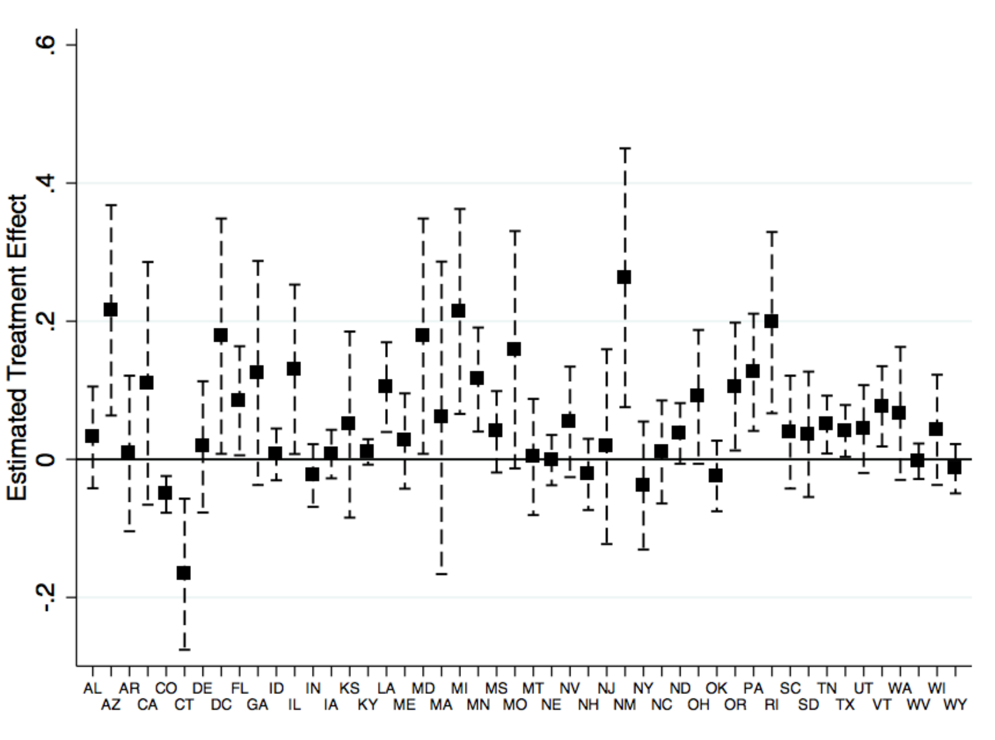
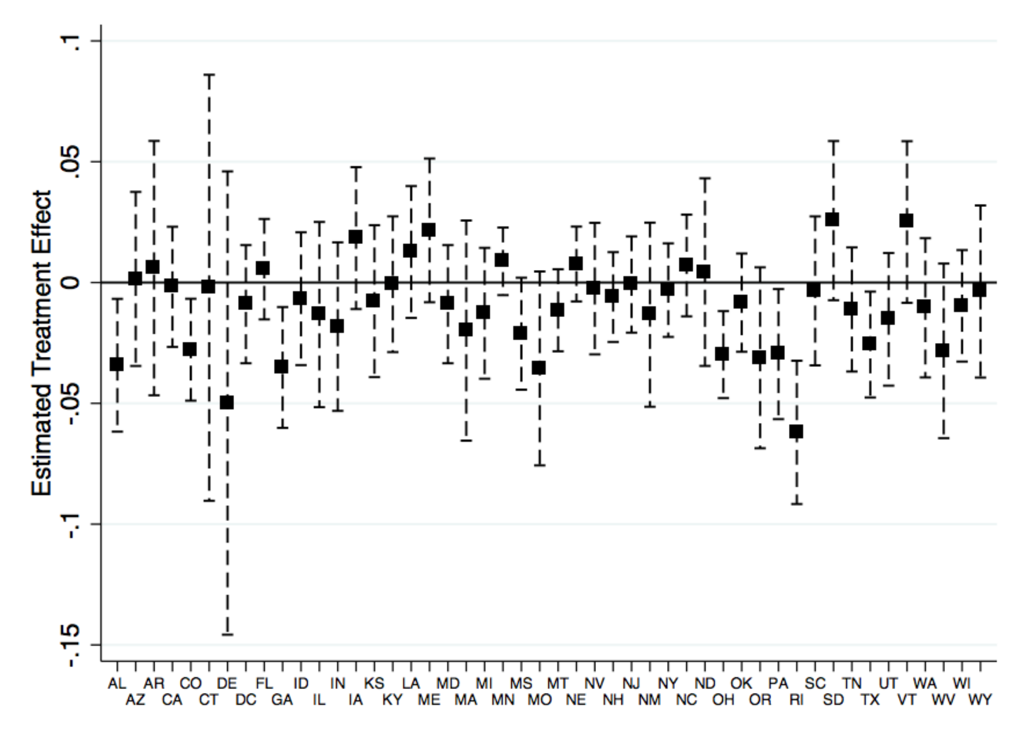


Figure A13
State-Specific Estimates of the Effect of
Employment-to-Population Ratios on the Fraction of Births to Mothers Age < 18



Appendix A.2

Additional State Characteristics and the Cyclicality of Health Outcomes

NOT INTENDED FOR PUBLICATION

Notes for all tables in Appendix A.2: Each observation represents a state. Its horizontal position is a measure of the state's characteristics and its vertical position is the estimated effect of county employment-to-population ratios on a health outcome. The size of each observation is proportional to the size of the population that it represents over the sample period. The reported correlations also uses population weights. For additional notes on the state-specific estimates, see Figure 2 or Appendix A.1. For matters of convenience, state poverty rates are based on the 1990 Census and the fraction of a state's adult population with a high school (college) education is based on the CPS from 1978–2006.

Figure A14
State "Not In Poverty" Rates and The Effects of County Economic Conditions on Mortality

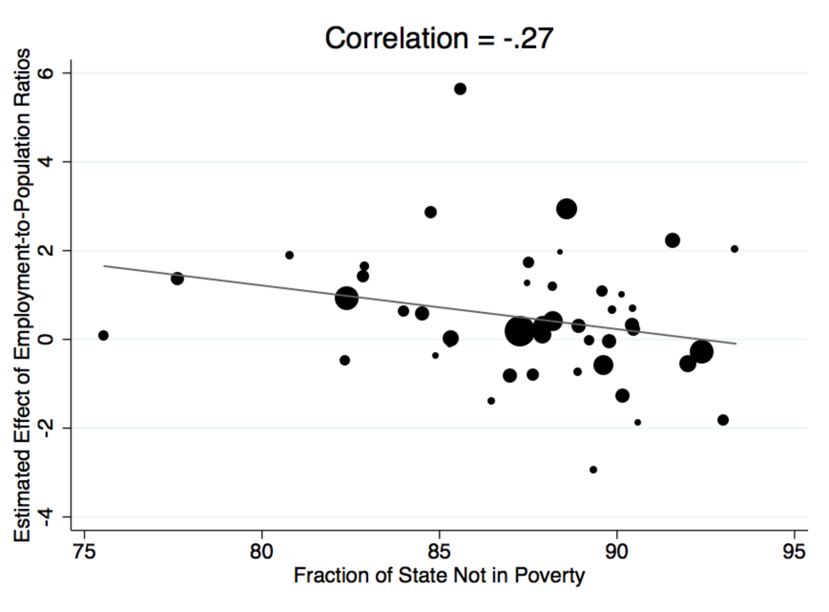


Figure A15
State Fraction with High School Education and The Effects of County Economic Conditions on Mortality

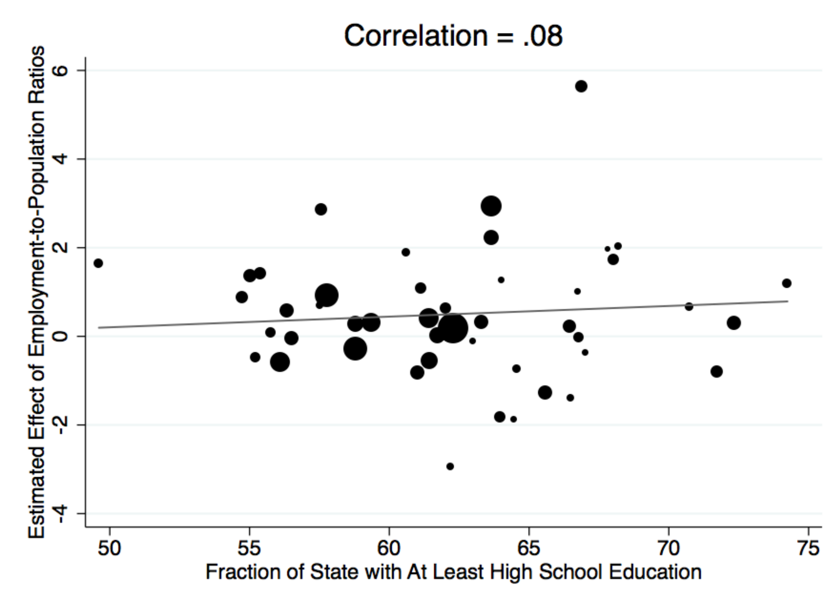


Figure A16
State Fraction with College Degree and The Effects of County Economic Conditions on Mortality

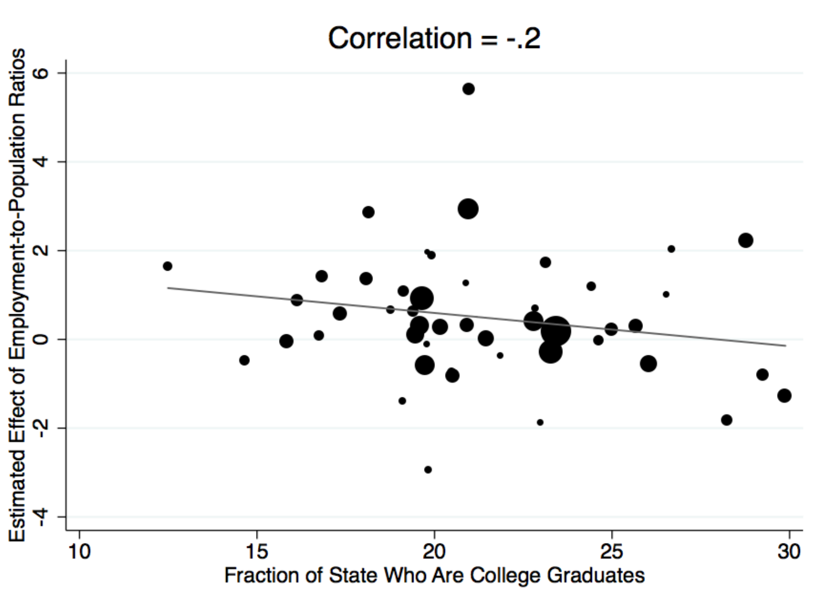


Figure A17
State "Not In Poverty" Rates and The Effects of County Economic Conditions on Other Health Outcomes

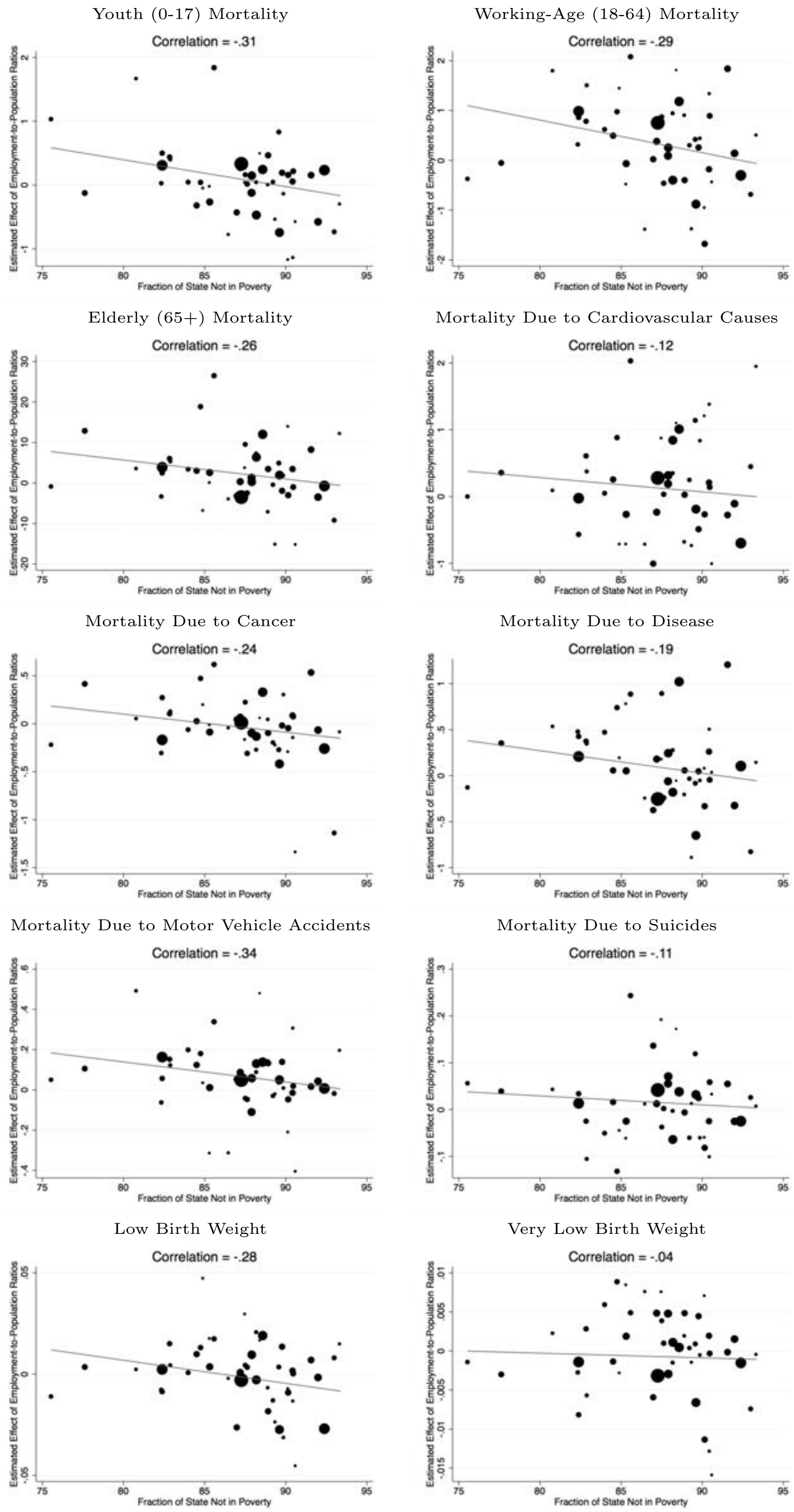


Figure A18
State Fraction with High School Education and The Effects of County Economic Conditions on Other Health Outcomes

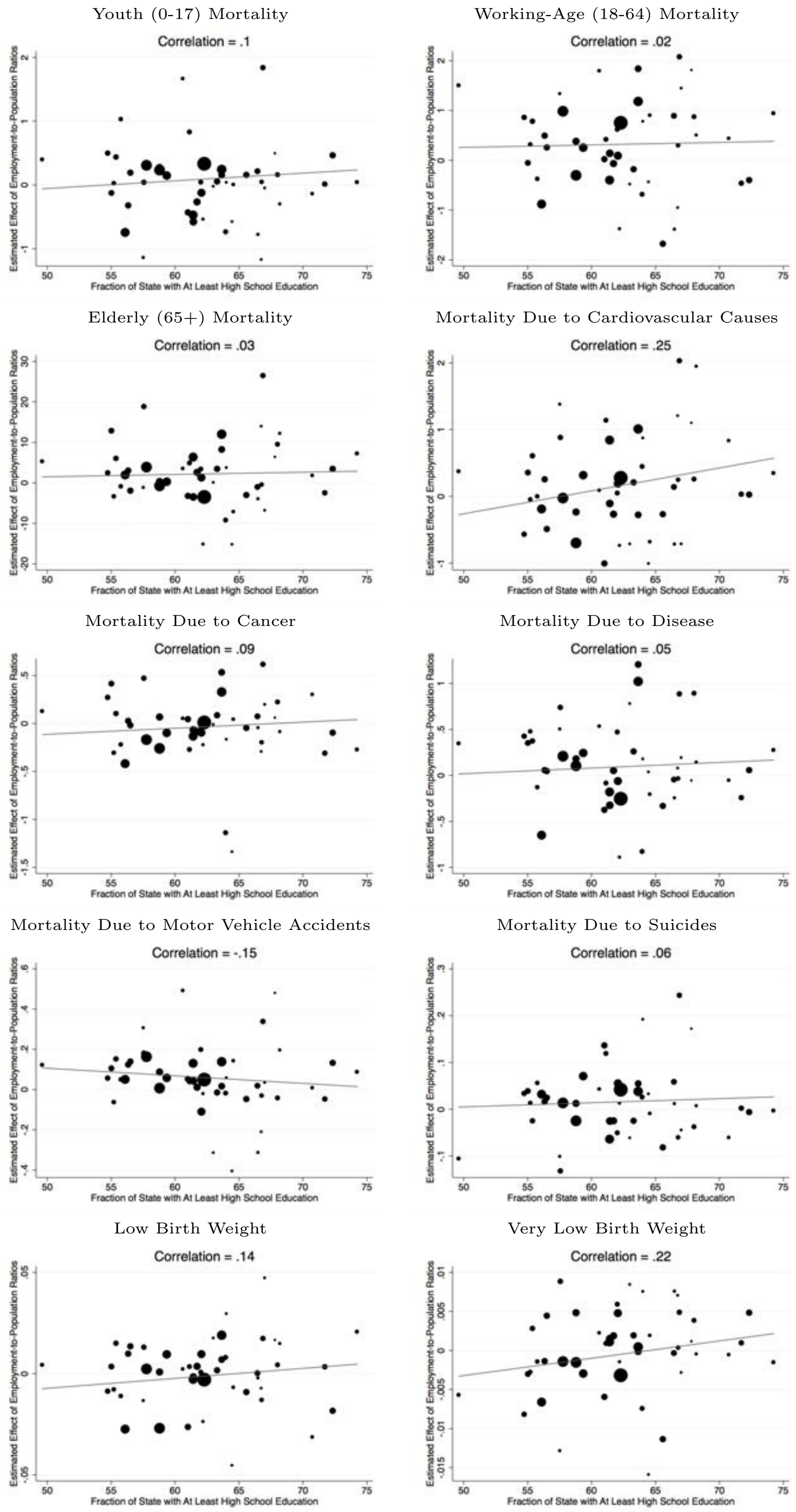


Figure A19
State Fraction with College Education and The Effects of County Economic Conditions on Other Health Outcomes