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RECESSIONS, POVERTY, AND MORTALITY IN THE UNITED STATES: 1993-2012

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Abstract
Prior studies suggest that higher unemployment rates reduce mortality, but newer research suggests this relationship may have attenuated in recent decades. Moreover, individual-level evidence shows a negative effect of economic adversity on survival. We revisit this question using county-level data and two additional macroeconomic measures: poverty rates and median incomes. Examining county-level mortality among non-elderly adults from 1993-2012, we find that higher unemployment has modest negative impacts on mortality, in contrast to prior work using older state-level data. More notably, county-level poverty rates and lower median incomes produce larger and consistently negative effects on mortality, both in the short-term and also for several years afterwards. These findings are consistent across multiple causes of death and for different subgroups of adults. While previous research has found that higher unemployment may produce small beneficial effects on survival, our analysis using more recent and granular data suggests this relationship no longer holds, and other economic measures such as median income and poverty rates provide stronger evidence that adverse economic conditions lead to higher mortality.

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Economic cycles may have important implications for population health. However, the direction of these effects is unclear. During economic downturns, household resources decline, which may lead to worsening access to medical care, nutritious food, and elements of basic physical well-being such as adequate shelter and heating. Alternatively, recessions reduce overall levels of employment, and work may be a primary cause of stress that can worsen cardiovascular and other health outcomes. More leisure time may also lead to better or worse health behaviors related to exercise, diet, smoking, and driving.

Previous evidence paints an inconsistent picture of these relationships, with conflicting findings on whether economic downturns lead to increased or decreased mortality. Several prior studies – including influential papers by Ruhm (2000; 2003; 2005; 2008) and Granados (2005) – use aggregated employment data at the state or national level to show a procyclical effect of macroeconomic conditions on mortality, with death rates increasing during periods of high employment. More recent research by Ruhm (2015), however, indicates that since 1990, this relationship in the U.S. no longer exists. Meanwhile, numerous studies have shown that low socioeconomic status and job loss are associated with adverse health outcomes at the individual level (Marmot et al., 1991; Hughes, McMunn, Bartley, & Kumari, 2015; Rosenthal, Carroll-Scott; Earnshaw, Santilli, & Ickovics, 2012). These conflicting findings create uncertainty about the overall impact of macroeconomic conditions on health. The literature also has focused almost exclusively on the effects of unemployment, which may not fully capture economic impacts for lower-income populations and those with major health limitations who are not in the workforce.

1 Like Ruhm and others, we at times frame our discussion around the notion of how recessions impact health, but our empirical approach focuses on more general fluctuations in several economic indicators, rather than the precise timing of an official recession as defined by the National Bureau of Economic Research.
Our study’s primary objective is to assess the relationship between several distinct economic indicators – unemployment rate, poverty rate, and median household income – and area-level mortality over the past 20 years among non-elderly adults. Using the U.S.’s detailed mortality files, obtained under agreement with the Centers for Disease Control and Prevention (CDC), we evaluated predictors of county-specific adult mortality rates from 1993-2012, a time of significant macroeconomic fluctuations in the United States. We estimated fixed-effects models to identify within-county (and alternatively, within-state) impacts of economic changes over time, with varying approaches to account for time trends at the national and state level. We also explored differential economic effects on mortality based on race, sex, and cause of death, as well as the impact of current economic circumstances versus the lagged impact of previous years’ economic conditions.

Our key findings are as follows. Within counties and states over time, unemployment rates over the past two decades demonstrate a weak and inconsistent effect on mortality, similar to recent findings from Ruhm (2015). In our preferred model, which adjusts for county fixed effects and year fixed effects, a 1-unit standard deviation (SD) increase in unemployment is associated with a 2.8% increase in all-cause mortality; other models using national or state-level time trends and either county- or state-level data show estimates ranging from -0.8% to 1.9%. Meanwhile, we find larger and more robust countercyclical mortality effects when examining other economic indicators. Median household income has the strongest effect on mortality, with an estimated mortality increase of 8.3% per SD decrease in median household income, while a one SD increase in the poverty rate is associated with a 3.7% increase in mortality. We conclude that the finding that recessions save lives no longer holds in the U.S., and that measures of
absolute resources such as the poverty rate or median income (rather than unemployment) provide even stronger evidence to the contrary – economic adversity increases mortality.

This general pattern is consistent for men and women, whites and non-whites, and holds across multiple causes of death including health-care amenable causes, cancer, suicide, and accidents. Lagged analyses show that higher poverty rates or lower median incomes in prior years are generally stronger predictors of higher mortality in subsequent years than same-year economic status, suggesting that the impacts of adverse macroeconomic conditions on health are increasingly harmful over time.

Section I reviews the literature on the relationship between economic conditions and mortality and explores the potential differences in this relationship based on alternative economic measures. Section II describes our data and methods. Section III presents the main results. Section IV discusses possible explanations for these findings and compares them to previous research. Section V concludes.

I. PREVIOUS RESEARCH ON ECONOMIC CYCLES AND MORTALITY

Widely cited analyses of aggregate and time-series data by Brenner (1973, 1975, 1979, 1987, 1995) demonstrated an inverse relationship between unemployment rates and mortality rates, with mortality increasing in step with unemployment rates. Unemployment has been shown to induce stress, cardiovascular disease, lung cancer, and suicide (Kasl, Cobb, & Brooks, 1968; Platt, 1984; Bjorklund, 1985; Townsend, Phillimore, & Beattie, 1988; Franks et al., 1991; Bartley, 1994; Morris, Cook, & Shaper, 1994; Wilkinson, 1996). Numerous other studies demonstrate the negative impact of lower socioeconomic status on mortality at the individual level (Marmot et al., 1991; Minchin, 1993; Geronimus et al., 1996). Lower income is a
particularly strong predictor of increased mortality among those under 65 and those at the bottom end of the income distribution (Backlund, Sorlie, and Johnson, 1996; McDonough et al., 1997; Dowd et al., 2010), and targeted cash transfers to single mothers has been shown to increase the longevity of their son’s lives, with the strongest results among the poorest mothers (Aizer et al., 2014). Persistent poverty is a stronger predictor of health risk than temporary episodes of poverty, and income losses have a greater effect on mortality than income gains (Benzeval & Judge, 2001).

However, several studies have demonstrated that economic downturns, as measured by the unemployment rate, have positive effects on health (Adams, 1981; Ruhm, 2000, 2003; Granados 2005). To correct for omitted variable bias in longitudinal analyses, Ruhm (2000, 2007) used state fixed effects and showed that declining unemployment was associated with higher cardiovascular-related mortality. International comparisons have produced similar findings. Gerdtham and Ruhm (2006) examined 23 OECD countries from 1960-1997 and found that when labor markets strengthen, mortality from multiple causes rise, controlling for year and location fixed effects, time trends, and demographics. Miller et al. (2009) found procyclical mortality patterns based on state unemployment rates, largely due to variations in motor vehicle accidents. Related studies by Evans and Moore (2011) and Snyder and Evans (2006) focus on the mortality effects of short-term changes in income rather than macroeconomic fluctuations. Their work shows that short-term income increases are associated with a rise in mortality, potentially due to increased levels of activity and consumption enabled by more income.

However, Ruhm and others have published findings indicating that in more recent decades, the pro-cyclical mortality pattern has weakened or gone away entirely. Ruhm (2015) examined the effect of unemployment on mortality in the U.S. from 1976-2010 using state-level
fixed effects and found that the protective effect of unemployment on mortality attenuated over the study period to a weak or null effect. Stevens et al. (2011) demonstrated an inconsistent impact of unemployment on health depending on the years studied, while McInerney & Mellor (2012) found similar results among the elderly. Concerning the geographic unit of analysis, Lindo (2014) focused on the impact of the level of aggregation when examining effects of economic conditions on health, observing that more granular data (such as county-level rather than state-level) can lead to more precise estimates of the effects of unemployment on mortality, though they may not capture spillover effects that may be better assessed by state-level analyses.

Here we broaden the scope of this previous work to consider two additional economic measures beyond unemployment: household median income and the poverty rate. What information does each of these measures of macroeconomic conditions capture? The unemployment rate is the number of individuals actively seeking work over the total number of people in the workforce, and therefore does not capture the non-employment mediated pathways between economic fluctuations and health, which may be particularly important for populations that rely on public assistance programs, people with disabilities, and those not seeking work. Median household income reflects the midpoint of the income distribution and therefore does capture these multifaceted aspects of a family’s resources, as well as changes in work hours or wages per hour, even holding employment status constant. Meanwhile, the poverty rate measures the percentage of individuals who have household incomes below a fixed value (approximately $23,000 in 2012 for a family of four.)

In other words, while median income

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2 The poverty rate, though commonly used, is an inexact term. The federal government uses two related definitions: the federal poverty thresholds, which are defined by the Census Bureau and used for all official poverty statistics put out by the government (including the county-level estimates used here); and the federal poverty guidelines, a simplified version of the poverty thresholds used by state and federal agencies in determining eligibility for public programs such as Medicaid. For more information, see: [http://aspe.hhs.gov/frequently-asked-questions-related-poverty-guidelines-and-poverty](http://aspe.hhs.gov/frequently-asked-questions-related-poverty-guidelines-and-poverty)
measures the 50th percentile of income, the poverty rate typically captures information on the 10-15th percentile of income (given the range of poverty rates observed in our dataset). Poverty rates are therefore more sensitive to variations in the lower end of the income distribution and also factor in sources of income not directly measured by unemployment rates.

There is ample theoretical and empirical evidence to suggest that the mortality impacts of these different measures might vary. Stress and lifestyle factors play particularly important roles in mediating the relationship between economic status and health (Brunner, 1997; Mokdad, Marks, Stroup, Gerberding, 2004). Lower-income individuals are more likely to smoke, less likely to have a regular source of care, and less likely to be physically active (CDC, 2012), and tobacco and physical inactivity are leading causes of death during our study period (Mokdad et al, 2004). Engagement in unhealthy behaviors may increase during times of economic hardship, though this differs by whether hardship is measured by employment status or income (Colman & Dhaval, 2013; Dhaval & Inas, 2012). For instance, Xu (2013) found that among populations with low levels of educational achievement, time-intensive activities such as physical activity, heavy drinking, and using health services occur less often when the employment rate rises, while less time-intensive behaviors such as cigarette smoking increase. However, the author also finds that cigarette smoking declines with income. Thus, different approaches to measuring economic conditions may be linked to different patterns of health behaviors.

All three indicators represent a potential pathway to obtaining safe housing, nutritious food, education, and health care, which are all strong predictors of health (Adler & Newman, 2002; Berkman & Glass, 2000; Hafner-Eaton, 1993). But they are not necessarily proxies for one another. Employment status does not necessarily dictate absolute income and those living in counties with the highest poverty rates and lowest median incomes may experience detrimental
neighborhood conditions, social environments, and psychosocial stressors despite being employed (Ross & Mirowsky, 2001; Berkman et al., 2001). Again, these three measures therefore likely capture different information relevant to the mortality impacts of macroeconomic conditions.

Our paper builds on previous research exploring the relationship between economic conditions and mortality by focusing on poverty rates and median income, in addition to unemployment rates. We also explore the impact of using granular county-level data in addition to state-level estimates. Finally, we explore the impact of a range of assumptions about time trends, since many existing models in the literature likely absorb much of the meaningful variation in local economic conditions that are critical in evaluating the link between the macroeconomy and population mortality.

II. DATA AND METHODS

A. Data

Our primary data come from the Centers for Disease Control and Prevention’s (CDC) Compressed Mortality File and vital statistics. Following Lindo (2014), we improve on prior analyses of economic cycles by presenting both a more granular level of analysis – county-level data – alongside state-level estimates, made possible through our access to restricted mortality files from the CDC. State-level estimates can mask significant economic heterogeneity, and a growing body of research shows the importance of location and the “built environment” to population health (Jackson, 2003; Casagrande et al., 2009). On the other hand, county-level estimates may not capture spillover effects within a state (Lindo 2014).
The Compressed Mortality File is a database containing information on all U.S. deaths in the prior year. The dataset is organized into county-level cells, specific to each year and population group, stratified by race, sex, and age group. For each county-specific race-sex-age cell, the dataset identifies the number of deaths occurring each year due to each specific cause of death, as indicated by the diagnosis code on official death certificates. The CDC then pairs this with information from the U.S. Census Bureau on each county’s population by race, sex, and age group to enable the calculation of annual mortality rates per 100,000 people. The publicly-available Compressed Mortality File suppresses all cells with fewer than 10 deaths. This effectively precludes analyses of subgroups and particular causes of death at the county-level. We obtained access to the uncensored data file, which is available by direct application to the CDC.

County- and year-specific economic measures were from the Census Bureau and Bureau of Labor Statistics (BLS). The poverty and income measures are derived from the Small Area Income Poverty Estimates (SAIPE). The SAIPE are produced from statistical models that include information from Census data, Bureau of Economic Analysis personal income estimates, federal income tax returns, participation in the Supplemental Nutrition Assistance Program (SNAP), and survey data from the Current Population Survey before 2005 and the American Community Survey after 2005 (U.S. Census Bureau; Bell et al., 2007). The SAIPE began to produce county-level measures of poverty on an annual or biennial basis starting in 1993. In 1994, there were no SAIPE estimates, and in 1996, SAIPE produced only state-level estimates, with annual county-level estimates thereafter. We used linear regression to impute the missing county-level income and poverty data for 1994 and 1996 as a function of county-level time

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3 Due to federal data use restrictions, the authors are prohibited by law from sharing this dataset. Those interested in obtaining these data can apply directly to the CDC via the following website: http://www.naphsis.org/Pages/VitalStatisticsDataResearchRequestProcess.aspx
trends and state poverty rates and median income rates, respectively, from 1993-1997. Unemployment estimates come from the BLS local area unemployment estimates. Our study period uses the full extent of available county-level economic estimates for each of our measures and the most recent mortality data available from the CDC, which produced an overall study period of twenty years, from 1993-2012. While county-level survey-based economic measures are likely subject to greater measurement error than state-level estimates, if this were a significant problem we would expect to observe attenuation bias in our county-level estimates. However, for most of our analyses, the county-level estimates were similar in magnitude or in some cases larger than the state-level estimates, suggesting this is not a key driver of our results.

Additional county- and year-specific measures (educational attainment and Hispanic ethnicity) were obtained from the Area Resource File (ARF), compiled by the Health Resources and Services Administration.

B. Analysis

Our baseline model was a linear regression with the natural logarithm of the all-cause mortality rate as the dependent variable. Secondary analyses considered causes of death in the following categories: cardiovascular disease, cancer, homicide, suicide, accidental injuries, and health-care amenable mortality (as defined by Sommers, Long, and Baicker, 2014, and adapted from Nolte & McKee, 2003). Health-care amenable mortality refers to causes of mortality that are most likely preventable or treatable by timely medical intervention (such as cancer, heart disease, and infections), and this measure may be responsive to changes in economic conditions.

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4 For 1994, this required using state-level estimates for poverty rates and median income from the Current Population Survey; for 1996, we used the SAIPE state-level estimates.
5 Our primary model used the log((Death Rate + 1) / 100,000) to avoid dropping observations with 0 deaths in a given year (4.5% of the county-level population-weighted sample). Linear models using deaths per 100,000 as the outcome or excluding values with 0 deaths in the log-linear model both produce similar overall findings.
because of the relationship between economic cycles, health insurance coverage, and receipt of medical care: during economic downturns, fewer people have private health insurance and public budgets tighten (Poterba 1994), which can increase cost-related barriers to obtaining needed medical care (Karaca-Mandic et al., 2013).

Our sample contained individuals between the ages of 20-64. The three alternative economic measures – county-year unemployment rate, poverty rate, and median household income (inflation adjusted to 2012 dollars) – were normalized into z-scores using population-weighted county-level estimates to facilitate direct comparisons of the magnitude of the coefficients.

Our primary models considered each economic indicator independently. Equation 1 shows the model for the county-year unemployment rate; analyses of poverty rate and median income were analogous.

\[
\ln(Mortality \ Rate_{ijkt} + 1) = \beta_0 + \beta_1 X_{ijk} + \beta_2 HispanicPct_{lt} + \beta_3 EducationCounty_{lt} \\
+ \beta_4 UnemploymentRate_{lt} + \partial Year_t + \Omega County_l + \varepsilon_{ijkt}
\]

Equation (1)

where \(i\) indexes age group, \(j\) race, \(k\) sex, \(l\) county, and \(t\) year. \(X_{ijk}\) is a vector of demographics (age group, race, and sex).\(^6\) \(HispanicPct\) is the county-year-specific percentage of the population that is Hispanic (from the ARF), since individual-level ethnicity was not collected by the CDC for the early years of our sample.\(^7\) \(EducationCounty\) is a vector of county-level percentages related to

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\(^6\) Race in the CDC mortality data are collected as follows: “Information included on the death certificate about the race and Hispanic ethnicity of the decedent is reported by the funeral director as provided by an informant, often the surviving next of kin, or, in the absence of an informant, on the basis of observation. Race and ethnicity information from the census is by self-report.” From: <http://wonder.cdc.gov/wonder/help/cmf.html#Racial%20Differences>, Accessed 15 May 2012.

\(^7\) Since 1999, the CDC has included information on ethnicity, in addition to race, though roughly 1% of deaths do not include any ethnicity information. Here, to use the full dataset from 1993-2012, our primary models do not use individual-level ethnicity information and instead adjust for the year-specific county Latino percentage of the population, following Sommers, Baicker, and Epstein (2012).
the educational attainment of the population: the percentage of adults (25 and older) with a high school diploma, and percentage with at least four years of college. The Census Bureau only puts out intermittent county-level estimates of educational attainment. We use the 1990, 2000, and 2006-2010 and 2008-2012 pooled estimates in the ARF, with linear extrapolation for the intervening years.\(^8\) \(\Omega\) is a vector of county fixed effects, and \(\delta\) is a vector of year fixed effects.

We tested alternative approaches to modeling time trends at a national and state level. The choice of these covariates is an important factor in assessing the implications of the model. Generally speaking, there are two primary sources of within-area variation in economic outcomes that can be used to identify the impact of macroeconomic conditions: 1) national shocks, such as during recessionary periods and/or the recent financial crisis; 2) local or state variation in economic performance over time, related to the rise and fall of particular regionally-focused industries or changing state economic regulations. Threats to identifying the effect of these plausibly exogenous macroeconomic forces come from factors such as secular trends in medical technology and selective in- or out-migration leading to changing demographics in a given area. Our model adjusts for the former using annual fixed effects, and for the latter using county-level controls for demographics including age, sex, race, ethnicity, and educational attainment. Models using both annual fixed effects and state-level trends absorb most of the meaningful variation in macroeconomic conditions. Accordingly, our primary model controls for time-invariant local features with county fixed effects, demographic factors as listed above,

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\(^8\) We treated the 5-year pooled estimates accordingly: for the years 2006-2007, we used the 2006-2010 pooled estimates. For 2008-2010 (the overlapping period of the two estimates) we took the average of the 2006-2010 and 2008-2012 pooled estimates. For 2011-2012, we used the 2008-2012 pooled estimates. The lack of year-specific measures of educational attainment introduce some measurement error and raise the possibility of non-linear shifts in education within counties that could be correlated with the economic measures and mortality outcomes studied here. This approach should capture large trends in educational attainment within counties, but may miss short-term changes.
and national trends using annual fixed effects. In sensitivity analyses, we tested the impact of adjusting for state-specific time trends instead.

We also tested the impact of using data aggregated to the state level, rather than county level, though previous research (Lindo 2014) suggests the latter produces more precise estimates and also better accounts for the within-state heterogeneity discussed earlier.

We then estimated a model incorporating all three measures simultaneously, as in Equation 2:

\[
\ln(Mortality\ Rate_{ijkt} + 1) = \beta_0 + \beta_1 X_{ijk} + \beta_2 HispanicPct_{lt} + \beta_3 EducationCounty_{lt} \\
+ \beta_4 UnemploymentRate_{lt} + \beta_5 MedianHouseholdIncome_{lt} \\
+ \beta_6 PovertyRate_{lt} + \delta Year_i + \Omega County_l + \epsilon_{ijklt}
\]

Equation (2)

Then, using our primary model (Equation 1), we conducted subgroup analyses examining each indicator by cause of death, race, sex, and age. We also examined the timing of economic influences on mortality by analyzing the impact of both the current year and the previous year’s level of each economic indicator on current mortality rates, or alternatively, lagged measures for up to four years prior, following Ruhm (2000) and discussed at more length in Section III.F below.

All analyses were weighted by the population size in each age-race-sex county cell, to yield appropriate population-level estimates, and we used robust standard errors clustered at the county level. Sensitivity analyses of our primary model using county-year clustering were nearly identical.

III. RESULTS
A. Descriptive Trends

Figure 1 depicts the trends of the three economic indicators and all-cause mortality in the U.S. from 1993 to 2012 for non-elderly adults, using normalized values for each measure. We also inverted median income to put it in same directionality as the other measures (i.e. higher = worse) for Figure 1, though we did not do so for the results in the regression tables. Unemployment, the poverty rate, and median income move in the expected directions during economic downturns, while the death rate remains more stable over time. The poverty rate and median income generally move in tandem during the study period, while the unemployment rate appears to be less correlated with the other measures. The normalized death rate improves when the poverty rate, unemployment rate, and median household incomes improves, though this relationship is less obvious during the recession of 2009.

B. Correlation Between Economic Measures

To explore the relationship between the three alternative economic measures in motivating our research question, we compare the correlation coefficients between the county-specific estimates for each indicator over time, from 1993-2012. Figure 2 presents these results. Over the full study period, the correlation between median income and poverty (-0.77) was stronger than that between unemployment and poverty (0.55) and unemployment and income (-0.38). Moreover, Figure 2 demonstrates that there has been a significant change in the relative correlations between these indicators over time. From 1993-2012, the absolute value of the correlation coefficient between unemployment and the other measures has generally been decreasing. Meanwhile, the relationship between median income and poverty has been stable and quite strong (nearly 0.8) throughout the study period. These divergent trends may partially
reflect decreases in labor force participation during the Great Recession, which affects the
denominator for the unemployment rate but not the poverty rate or median income. A direct
comparison of the county employment-to-population ratio over the same time period yields a
somewhat stronger correlation with poverty rates (-0.68) and median income (0.59) than the
unemployment rate, but still well below the strong correlation between median income and
poverty. These findings support the hypothesis that the poverty rate and median income capture
impacts of the economy that are likely distinct from the unemployment rate.

C. All-Cause Mortality

Table 1 displays the relationship between each economic indicator and mortality in
models using county-level and state-level data, respectively. In our preferred model (Model 1)
using year and county fixed effects, within-county changes in the unemployment rate produce
significant though modest increases in the county-level mortality rate – with a one-unit standard
deviation increase in unemployment (corresponding to 2.78 percentage points) leading to a 2.8%
increase in all-cause mortality. Alternative county-level specifications with a national linear
time trend, area time trends, or inclusion of other economic measures simultaneously
(‘multivariate model’) all produce smaller though still significant point estimates ranging from
1.4-1.8%. In state-level analyses, however, the relationship between unemployment and
mortality is weaker and not statistically significant in the primary model or the multivariate
model, consistent with Ruhm (2015)’s findings of an attenuated link between employment and
mortality over the past 20 years.

In contrast, we find larger and more robust estimates of a strong link between lower
median incomes and higher mortality, and higher poverty rates and higher mortality. In our
preferred model, a one-SD decrease in median income (corresponding to $14,195 in 2012
dollars) leads to an 8.3% increase in all-cause mortality, and a one-SD increase in the poverty rate (corresponding to 5.47 percentage points) leads to a 3.7% higher death rate. These results are robust in state and county-level analyses using a national time trend or area time trends. In the multivariate model, median income is a significant predictor of mortality ($\beta=-6.5\%$) in the county-level analysis, while poverty rate is a significant predictor ($\beta=6.0\%$) in the state-level analysis. Given the strong correlation between these two measures as shown in Figure 2, it is not surprising that the estimates for one or the other are attenuated in a regression model that includes both simultaneously.

D. Subgroup Analyses

We then examined these patterns for different subgroups based on race and sex. Table 2 presents the results using our preferred county-level specification. With the exception of the poverty rate for non-whites, which is not significantly associated with mortality, all three measures show the same basic pattern as in the full population: higher poverty rates, lower median income, and higher unemployment are all associated with higher mortality. Mortality rates among men are somewhat more responsive to economic conditions than women, though estimates are significant for both groups. Median income is the strongest predictor of within-county mortality variation for all for subgroups, with a 6.1-10.3% increase in mortality per SD decrease in median income, versus a 0.8-4.6% increase per SD of poverty and a 2.2-3.0% increase per SD of unemployment.

E. Causes of Death

Table 3 presents the analyses by cause of death. Here, since more of the observations have zero values than in analyses of all-cause mortality, we present both the log model and a linear model, with deaths expressed per 100,000 adults. In general, the findings for the linear and log models were similar. For all causes of death other than cardiovascular disease, the same basic pattern holds: high unemployment, lower median income, and higher poverty rates lead to significant higher death rates.

The majority of the changes in death rates tied to these economic measures occur in the category of “health care amenable deaths,” which represent two-thirds of deaths in the sample. The significant link between poverty and income with healthcare-amenable mortality is consistent with the notion that recent economic downturns have resulted in worsening access to health care (Kenney et al., 2012), as well as evidence from Massachusetts’ 2006 health reform law, in which expanded access to health care reduced mortality from these causes (Sommers, Long, & Baicker, 2014).

Meanwhile, consistent with analyses of recent data (Ruhm, 2015), the previously protective effect between high unemployment and accidental deaths (Miller et al. 2009) is no longer evident. Accidental deaths – including transportation deaths as well as falls, poisonings, and other causes – have become more common during times of economic downturns, coinciding with rising national concerns regarding rates of drug overdoses (CDC, 2012). Table 3 shows that suicide rates are strongly responsive to recessions, with suicides increasing with economic distress as measured by all three indicators, a finding consistent across most previous research in

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9 These analyses include a dummy variable for the years 1997-1998 to account for any changes in classification due to the transition from the ICD-9 to ICD-10 diagnosis codes.
this area (Ruhm 2000; 2002; Miller et al., 2009). Homicide rates also rise in response to worsening economic conditions. Associations between all three measures and cardiovascular death rates are inconsistent and generally small.

F. Timing of Economic Measures

We also examined the impact of adding a one-year lag of each economic indicator. Table 4 shows the estimated impact on mortality of the economic indicators from both the current year and previous year, and Table 5 extends this analysis to include lagged measures for the previous four years, following the approach in Ruhm (2000). For both unemployment and poverty, the lagged measures are stronger predictors of current-year mortality than the present-year measure. For median income, both the lagged and current year measures are significant predictors of current mortality. Meanwhile, Table 5 shows that lagged measures as far back as 4 years are significant predictors of current-year mortality for all three measures. For all three measures, worsening economic performance in previous years is linked to higher current-year mortality to a greater extent than current economic performance. However, the use of several years’ worth of lagged measures necessarily truncates the study period, and shorter time periods for analysis may yield less stable estimates on the relationships between economic factors and mortality (Ruhm 2015). Nonetheless, these findings support an interpretation that economic adversity has a cumulative negative impact on health that may be larger over time, consistent with evidence from individual-level studies of unemployment and poverty (Lynch, Kaplan, & Shema, 1997; Benzeval & Judge, 2001).

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10 Repeating this analysis without the year 2001 – which had a noticeable uptick in homicides due to the attacks of September 11th – produces similar results.
IV. DISCUSSION

A. Different Health-Related Properties of Economic Indicators

Using nationwide county-level data over a 20-year period, we find that three distinct economic indicators produce a similar pattern of findings – that economic downturns are bad for population health – with the unemployment rate the weakest predictor of this effect and median household income the strongest. This represents a different pattern than noted in numerous studies of older data from the U.S., and notably, from a body of literature that has focused almost entirely on the unemployment rate. Unemployment is a commonly-used measure of the health of the economy, but our findings show that it is generally the least predictive of mortality for non-elderly adults and is not significantly associated with mortality in several models. These findings suggest that if researchers are interested in examining the impact of macroeconomic conditions on health, unemployment rates should not be the sole or even primary indicator.

Why do these measures produce different estimates on the impact of macroeconomic conditions on mortality? Mortality risk is not evenly distributed in the population, even after adjusting for obvious covariates like age, race, and sex. Death rates are markedly higher among low-income individuals and those with chronic diseases (Galea et al., 2011), who are much less likely to be attached to the workforce in the first place. For many such individuals – who disproportionately drive population-level estimates of mortality by accounting for a higher share of deaths each year – employment status is a less relevant measure of economic circumstances than poverty rates or income. Unemployment also may not capture other important dimensions of an economic downturn, such as being forced to work fewer hours or at lower pay, elements captured more accurately by income or poverty measures.
Moreover, many poor or chronically ill individuals do not depend on wages for their income, but instead rely on public assistance programs. Such programs are often scaled back or reduced due to budget pressures when state and local tax revenues decline (Poterba 1994, Bohn and Inman 1994), and median income is likely a better gauge of changes in the overall tax base than the unemployment rate or the poverty rate. Finally, though the relationship between health insurance and health remains somewhat controversial (Baicker et al. 2013, Sommers, Baicker, and Long 2014, Levy and Meltzer, 2008), direct provision of health care via charity care or Medicaid may suffer during times of fiscal austerity, and recessions can lead to reduced health care utilization among insured individuals facing significant out-of-pocket costs (Karaca-Mandic et al., 2013).

B. Comparison with Prior Research

Placing our results in context, many of our findings are consistent with previous research. Early work by Brenner found countercyclical relationships between the strength of economies and mortality when examined in cross-section. Ruhm and others added state-level fixed effects to their models to reveal a procyclical impact of unemployment on mortality, but more recently showed that this effect is weak or non-existent in state-level analyses with data since 1990. Our work replicates this important finding. In addition, our findings go beyond Lindo’s (2014) consideration of the level of data aggregation by demonstrating the importance of considering economic indicators other than the unemployment rate.

Our findings support the robust body of work demonstrating an income-based gradient of health such that more income is associated with better health. This contrasts with findings from Evans and Moore (2011), though the issue may be primarily one of time frame. Transient
increases in mortality directly following income receipt captures fluctuations on the timescale of
days to weeks, whereas our results measure the impact of changes in yearly income or poverty
rates. In addition, the magnitude of the findings are quite disparate: for instance, in one of their
analyses Evans and Moore report a 0.29% increase in annual mortality due to a 5.5% increase in
income (an elasticity of 0.05), compared to our preferred estimate of an 8.3% decrease in
mortality per standard deviation of additional median annual income (an elasticity of 0.33),\(^\text{11}\)
suggesting that these short-term consumption-driven increases in mortality are far outweighed in
the longer-term by the adverse impact of worsening economic conditions.

The literature examining the effects of economic fluctuations on health among subgroups
of race and sex is inconsistent. Hoynes (2000) found that the health of non-whites and less-
educated populations was more responsive to changes in local labor market conditions compared
to white populations with higher levels of education. Granados (2005) posits that economic
fluctuations may have larger effects on non-whites and women because historically, these groups
were integrated into the paid labor market later on in the development of the modern American
workforce and are hired for lower quality positions compared to their majority counterparts.
More recently, Ruhm (2015) finds that the protective effect of unemployment declined faster for
men than women over his study period. We found that all three measures generally showed a
detrimental effect of worsening economic conditions, driven primarily by median household
income, with only minor differences across subgroups.

Like most of the previous ecological analyses of macroeconomic conditions and
mortality (national, state, or here county-level), our analysis is potentially subject to omitted
variable bias if there are factors systematically associated with these economic measures and

\(^{11}\) The sample-wide median income in 2012 dollars was $56,884, and the standard deviation was $14,195, indicating
an 8.3% decrease in mortality for a 25% increase in median income.
mortality that are not captured by the observable demographic controls, time trend and/or year fixed effects, and county fixed effects. One possibility is selective migration, which could lead people of different health states to move for economic opportunities in other states. In Ruhm’s original work on this topic, he finds little evidence that interstate migration patterns produce significant bias in this regard (Ruhm 2000), suggesting this is not likely to be a major source of bias for our analysis. In addition, we control directly for many of the factors likely to be closely correlated with such migration patterns – such as educational differences and Latino ethnicity – thus reducing the likelihood that migration explains our primary findings.

Related to the timing of these economic impacts on health, we also examined the effects of including one-to-four year lags of economic indicators in our models. For all three measures, previous years’ measures were comparable or even stronger predictors of higher mortality than current year measures, consistent with previous evidence demonstrating the potential cumulative impact of factors such as stress, limited access to health services, and unhealthy environments (Ayanian et al., 2000; Juster, McEwan, & Lupien, 2010, Gustafsson et al. 2014).

V. CONCLUSION

The relationship between economic conditions and mortality has been an area of significant interest in the economics and public health literature, with several major strands of research showing apparently conflicting patterns: a protective effect of unemployment at the population level (though weakening in recent years), very short-term increases in mortality from additional income receipt, contrasted with more generally harmful effects of economic adversity at the individual level. Here, we add important new evidence to this literature. Using county-level data from the past 20 years, we find modest and generally harmful effects of unemployment
on mortality, in contrast to the procyclical effects observed in older data. When considering the poverty rate or median income, our findings are stronger and more robust, consistently showing economic adversity to be a significant risk factor for death, for several major causes of death and for both men and women. Overall, the procyclical impact of the unemployment rate noted in previous studies no longer seems to characterize the U.S. economy and population health. Meanwhile, direct measures of household resources such as the poverty rate or median income are stronger predictors of population health that show a consistent pattern in the opposite direction: adverse economic conditions lead to worse health over time.
REFERENCES


Table 1. Associations Between Economic Measures and All-Cause Mortality Among Adults 20-64 from 1993-2012

<table>
<thead>
<tr>
<th>Model</th>
<th>Area-Year Economic Measures</th>
<th>Unemployment Rate</th>
<th>Median Household Income</th>
<th>Poverty Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td><strong>County Level</strong></td>
<td><strong>State Level</strong></td>
<td><strong>County Level</strong></td>
<td><strong>State Level</strong></td>
</tr>
<tr>
<td>(1) Area Fixed Effects, Annual Fixed Effects</td>
<td>.028***</td>
<td>.015</td>
<td>-.083***</td>
<td>-.044**</td>
</tr>
<tr>
<td></td>
<td>(.008)</td>
<td>(.011)</td>
<td>(.022)</td>
<td>(.017)</td>
</tr>
<tr>
<td>(2) Area Fixed Effects, Annual Time Trend</td>
<td>.018***</td>
<td>.013***</td>
<td>-.093***</td>
<td>-.058***</td>
</tr>
<tr>
<td></td>
<td>(.003)</td>
<td>(.005)</td>
<td>(.017)</td>
<td>(.013)</td>
</tr>
<tr>
<td>(3) Area Fixed Effects, Area Time Trends†</td>
<td>.015***</td>
<td>.019***</td>
<td>-.047***</td>
<td>-.058***</td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td>(.004)</td>
<td>(.012)</td>
<td>(.005)</td>
</tr>
<tr>
<td>(4) Area Fixed Effects, Annual Fixed Effects, Multivariate – all three measures simultaneously</td>
<td>.014**</td>
<td>-.008</td>
<td>-.065***</td>
<td>.008</td>
</tr>
<tr>
<td></td>
<td>(.007)</td>
<td>(.007)</td>
<td>(.019)</td>
<td>(.014)</td>
</tr>
</tbody>
</table>

Notes:
***p<0.01, **p<0.05, *p<0.10
Results show estimated coefficients and (SE). Outcome is specified as the natural log of [all cause mortality rate (deaths per 100,000) + 1]. Each economic measure is analyzed one at a time in its own regression, with the exception of Model 4. All models adjust for race/ethnicity, age, sex, and education.
† Area time trends for both state and county-level analyses were specified as interaction terms between state dummies and an annual time trend.
Table 2. Associations Between County-Level Economic Measures and All-Cause Mortality Among Adults 20-64, by Race and Sex

<table>
<thead>
<tr>
<th>Population</th>
<th>Mean Deaths per 100,000</th>
<th>County-Year Economic Measures</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Unemployment Rate</td>
<td>Median Household Income</td>
<td>Poverty Rate</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(SE)</td>
<td>(SE)</td>
<td>(SE)</td>
</tr>
<tr>
<td>Whites</td>
<td>323.5</td>
<td>.026***</td>
<td>-.085***</td>
<td>.046***</td>
</tr>
<tr>
<td></td>
<td>(.007)</td>
<td>(.022)</td>
<td>(.016)</td>
<td></td>
</tr>
<tr>
<td>Non-Whites</td>
<td>393.6</td>
<td>.022*</td>
<td>-.084***</td>
<td>.008</td>
</tr>
<tr>
<td></td>
<td>(.12)</td>
<td>(.026)</td>
<td>(.010)</td>
<td></td>
</tr>
<tr>
<td>Men</td>
<td>423.1</td>
<td>.030***</td>
<td>-.103***</td>
<td>.040**</td>
</tr>
<tr>
<td></td>
<td>(.009)</td>
<td>(.026)</td>
<td>(.016)</td>
<td></td>
</tr>
<tr>
<td>Women</td>
<td>251.7</td>
<td>.026***</td>
<td>-.061***</td>
<td>.033***</td>
</tr>
<tr>
<td></td>
<td>(.008)</td>
<td>(.020)</td>
<td>(.012)</td>
<td></td>
</tr>
</tbody>
</table>

Notes:
***p<0.01, **p<0.05, *p<0.10
Results show estimated coefficients and (SE). Outcome is specified as the natural log of [all cause mortality rate (deaths per 100,000) + 1]. All models adjust for race/ethnicity, age, sex, education, year fixed effects, and county fixed effects.
Table 3. Association Between County-Level Economic Measures and Mortality by Cause of Death

<table>
<thead>
<tr>
<th>Cause of Death</th>
<th>Mean Deaths per 100,000</th>
<th>County-Year Economic Measures</th>
<th>Unemployment Rate</th>
<th>Median Household Income</th>
<th>Poverty Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Linear Model</td>
<td>Log Model</td>
<td>Linear Model</td>
<td>Log Model</td>
</tr>
<tr>
<td>All-Cause Mortality</td>
<td>340.6</td>
<td>6.5*** (1.9)</td>
<td>.028*** (.008)</td>
<td>-21.0*** (4.8)</td>
<td>-.083*** (.022)</td>
</tr>
<tr>
<td>Health care amenable</td>
<td>226.8</td>
<td>4.7*** (1.2)</td>
<td>.027*** (.007)</td>
<td>-12.1*** (3.0)</td>
<td>-.054*** (.019)</td>
</tr>
<tr>
<td>Cardiovascular disease</td>
<td>66.6</td>
<td>-0.1 (0.4)</td>
<td>.006 (.005)</td>
<td>-0.3 (.7)</td>
<td>.004 (.013)</td>
</tr>
<tr>
<td>Cancer</td>
<td>97.5</td>
<td>0.7*** (0.2)</td>
<td>.008*** (.004)</td>
<td>-1.9*** (0.5)</td>
<td>.002 (.010)</td>
</tr>
<tr>
<td>Homicide</td>
<td>8.4</td>
<td>0.5** (0.2)</td>
<td>.035*** (.012)</td>
<td>-1.4*** (0.5)</td>
<td>-.107*** (.035)</td>
</tr>
<tr>
<td>Suicide</td>
<td>14.6</td>
<td>0.6*** (0.1)</td>
<td>.049*** (.009)</td>
<td>-1.3*** (0.3)</td>
<td>-.094*** (.029)</td>
</tr>
<tr>
<td>Accidents</td>
<td>34.6</td>
<td>1.0*** (0.4)</td>
<td>.046*** (.012)</td>
<td>-2.9*** (1.0)</td>
<td>-.112*** (.039)</td>
</tr>
</tbody>
</table>

Notes:
***p<0.01, **p<0.05, *p<0.10
Results show estimated coefficients and (SE). Linear model specifies each outcome as deaths per 100,000. Log model outcome is specified as the natural log of [all cause mortality rate (deaths per 100,000) + 1]. All models adjust for race/ethnicity, age, sex, education, year fixed effects, and county fixed effects.
Table 4. Associations Between Economic Measures and Mortality With A One-Year Lag

<table>
<thead>
<tr>
<th>Age</th>
<th>Unemployment Rate</th>
<th>Median Household Income</th>
<th>Poverty Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Previous Year</td>
<td>Current Year</td>
<td>Previous Year</td>
</tr>
<tr>
<td></td>
<td>.030*** (.007)</td>
<td>-.04 (.005)</td>
<td>-.033*** (.012)</td>
</tr>
<tr>
<td>Adults 20-64</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>County-Level</td>
<td>.023** (.010)</td>
<td>-.09 (.008)</td>
<td>-.003 (.012)</td>
</tr>
<tr>
<td>State-Level</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes:

***p<0.01, **p<0.05, *p<0.10

Results show estimated coefficients and (SE). Outcome is specified as the natural log of [all cause mortality rate (deaths per 100,000) + 1]. Each economic measure is analyzed separately, but regression models adjust simultaneously for previous year and current year level of the economic measure in question. All models adjust for race, age, sex, year fixed effects, and county-level fixed effects.
Table 5. Associations Between Economic Measures and Mortality With One-through-Four Year Lags

<table>
<thead>
<tr>
<th>Age</th>
<th>Unemployment Rate</th>
<th>Median Household Income</th>
<th>Poverty Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>County-Level</td>
<td>State-Level</td>
<td>County-Level</td>
</tr>
<tr>
<td>Adults 20-64</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Current Year</td>
<td>-.007 (.005)</td>
<td>-.007 (.008)</td>
<td>-.018* (.11)</td>
</tr>
<tr>
<td>1-Year Lag</td>
<td>.003 (.005)</td>
<td>-.002 (.007)</td>
<td>.000 (.009)</td>
</tr>
<tr>
<td>2-Year Lag</td>
<td>.003 (.005)</td>
<td>.001 (.007)</td>
<td>-.018* (.009)</td>
</tr>
<tr>
<td>3-Year Lag</td>
<td>-.009* (.005)</td>
<td>-.010 (.008)</td>
<td>-.045*** (.10)</td>
</tr>
<tr>
<td>4-Year Lag</td>
<td>.038*** (.008)</td>
<td>.040*** (.012)</td>
<td>-.011 (.010)</td>
</tr>
</tbody>
</table>

Notes:
***p<0.01, **p<0.05, *p<0.10
Results show estimated coefficients and (SE). Outcome is specified as the natural log of [all cause mortality rate (deaths per 100,000) + 1]. Each economic measure is analyzed separately, but regression models adjust simultaneously for previous years (1-4) and current year level of the economic measure in question. All models adjust for race, age, sex, year fixed effects, and county-level fixed effects.
Notes: Graph shows the mean normalized value for each outcome by year (with median income inverted to place it in the comparable orientation as the other measures).
Figure 2. Absolute Value of Correlation Coefficients between County-Level Unemployment, Median Income, and Poverty from 1993 to 2012

Notes: Graph shows the absolute value for the population-weighted correlation coefficients (ages 20-64) between each pair of economic measures, by year. 1994 data are omitted since the SAIPE dataset does not contain poverty or median-household estimates for that year.