County-level Unemployment Change and Trends in Self-rated Health

Jennifer Malat and Jeffrey M. Timberlake

University of Cincinnati

Recent research using national-level data finds that economic recessions are associated with improved population health in the United States. The present study utilizes data from Ohio to assess whether these conclusions hold at the county level, occur immediately at the onset of a recession, and vary by education and race. The data show that at the beginning of the period, higher cross-sectional unemployment rates were associated with worse average self-rated health. Yet, as unemployment rapidly increased over the study period, average health improved. The rate at which unemployment rates rose had less effect on those with college degrees compared to those with the least education. For whites, slower rate of unemployment growth was associated with more rapidly improving average self-rated health. However, blacks’ self-rated health trended more strongly positive in locations with rapid unemployment growth. The paper concludes by discussing implications for future research on how economic conditions affect health.

The United States entered a deep recession in late 2008. In the six-month period between August 2008 and January 2009, the seasonally adjusted national unemployment rate rose 22 percent (from 6.2 percent to 7.6 percent) (Bureau of Labor Statistics, United States Department of Labor 2010). Some states faced more rapid growth in unemployment. In the state of Ohio, unemployment rose by 31 percent (from 6.7 percent to 8.8 percent), and 7 of Ohio’s 88 counties experienced a doubling or greater increase in unemployment (tabulations from Ohio Department of Job and Family Services 2009).

Early research on economic conditions suggested that recessions are associated with worse physical health and higher mortality (Brenner 1973; Brenner and Mooney 1983; Catalano and Dooley 1977). However, more recent analyses have challenged these findings (e.g., Chay and Greenstone 2003; Dehejia and Lleras-Muney 2004; Granados 2005; Granados and Diez-Roux 2009; Laporte 2004; Ruhm 2003; Ruhm 2005). Initially researchers debated whether the newer, counterintuitive results were valid (Catalano 2009; Granados and Diez-Roux 2009; Smith 2005). Currently, the weight of the empirical evidence suggests that, in the United States at least, 1 when

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1This paper focuses mainly on studies of the U.S. population, because variation in the nature of government welfare programs may moderate the effect of economic change on health (Stuckler et al. 2009).

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Correspondence should be addressed to Jennifer Malat, Department of Sociology, University of Cincinnati, Cincinnati, OH 45221-0378, USA. E-mail: Jennifer.Malat@uc.edu
the economy has grown health problems and mortality rates have increased, and when economic growth has slowed, health problems and mortality rates have decreased (Catalano et al. 2011).

As noted in a recent review, many questions remain about the relationship between economic change and population health (Catalano et al. 2011). In order to understand the counterintuitive relationship, we need to establish the conditions under which the relationship exists, the timing of the effect, and whether the relationship is consistent across social groups. To that end, we address three specific issues. First, we evaluate whether negative economic changes at the local level, rather than national level, also positively affect health. Second, we contribute to understanding the timing of health effects by examining trends in average self-rated health over a short interval at the onset of a recession. Third, we assess race and education differences in the effect of rising unemployment. Because the causes of the counterintuitive relationship between recession and health have not been identified, the results of our analysis contribute to uncovering the mechanisms affecting the relationship between the economy and health. The analysis uses data from a large telephone survey of all Ohio counties that was in the field from August 6, 2008, until January 24, 2009. This period includes the onset of a deep recession. The results provide insight into the relationship between recession and health and suggest directions for future research.

BACKGROUND

Several recent studies convincingly conclude that higher unemployment rates are associated with lower population mortality and improved health (Chay and Greenstone 2003; Dehejia and Lleras-Muney 2004; Granados and Diez-Roux 2009; Laporte 2004; Ruhm 2003; Ruhm 2005). For example, Granados (2005) analyzed national mortality statistics and economic indicators for the last century. His research demonstrated that between 1900 and 1996 mortality rates were lower for all major causes of death, except suicide, when unemployment rates were rising and when the gross domestic product growth was lower, with the opposite trend during good economic times. While Granados’ research examines mortality, studies that employ alternative indicators of health, such as self-rated health, disability days, and obesity, find similar patterns over the shorter intervals for which other measures are available. Because findings are consistent, we refer to this body of research as research on economic change and “health.”

While many researchers speculate about the causes of the association between economic trends and health, few empirical studies test specific hypotheses (Catalano et al. 2011). Environmental conditions may have accounted for some of the change in mortality during recent recessions. Studies show that there were fewer traffic injuries (Ruhm 2005) and less infant death linked to air pollution (Chay and Greenstone 2003) in recent recessions. Other authors have looked at lifestyle changes, speculating that more free time and less expendable income may change health behavior. Indeed, studies find that during recent recessions, physical activity increased and alcohol consumption decreased (Dee 2001; Ruhm 2005). These studies offer useful, though partial, explanations for change in mortality during specific periods. Unfortunately, this small body of empirical research cannot support a comprehensive theory of why recessions are associated with better health.

Broader theoretical work in medical sociology can provide a starting point for developing a theory of how economic trends affect health. Seeking to explain persistent inequality in health, Link and Phelan (1995) explicated the theoretical perspective that social conditions
are a fundamental cause of disease, a general perspective on disease that was not new (e.g., Frazier 1925; McKeown 1976). Link and Phelan (1995) point out that as major causes of death change, and knowledge about and access to treatment of disease change, socially-advantaged people (e.g., those with better education, the white race) continue to enjoy better health. Link and Phelan’s theory (1995) and empirical research (e.g., Phelan et al. 2004), as well as the research it spawned (e.g., Chang and Lauderdale 2009; Warren and Hernandez 2007), suggest that reliance on historically-specific factors will not produce a comprehensive theory of long-term patterns in health. To date, the explanations for the association between recession and health have been based on particular recessionary periods. Consequently, they are unlikely to lead to an adequate explanation for the pattern over the last century. It is beyond the scope of this paper to develop a theoretical explanation that accounts for the long-standing relationship between economic trends and health in the United States. Rather, this paper draws on the theory that social factors are a fundamental cause of disease to posit that social context and social status affect health during a time of rapidly rising unemployment. In doing so, we advance the effort to understand the counterintuitive relationship between health and economic cycles.

Timing

One perplexing issue is whether a time lag exists between experiences during economic cycles and resulting health outcomes. Increases and decreases in mortality from cancer or cardiovascular disease, for instance, would seemingly be linked to past experiences (McKee-Ryan et al. 2005). Some authors argue that while this is true, mortality is often triggered by a significant contemporaneous event, which supports use of non-lagged mortality measures (Granados 2005). These authors also point out that studies of both morbidity and mortality empirically support use of concurrent measures of economic conditions and health (e.g., Granados 2005; Ruhm 2003). To improve understanding of the timing of changes in health status, the present study examines change in average self-rated health during a six-month period during which a rapid rise in the unemployment rate occurs. Self-rated health is a useful measure for our study of trends over a short interval, because it is a global measure of health that mirrors objective measures of health as well as mortality (Idler and Benyamini 1997) and is responsive to recent changes in individuals’ health and lifestyle (Rohrer et al. 2009).

Geographic Context

Most recent studies documenting a positive effect of economic recession have relied on recession indicators at the national level (e.g., Chay and Greenstone 2003; Dehejia and Lleras-Muney 2004; Edwards 2008; Laporte 2004; Granados 2005; Ruhm 2005). Yet, when theorizing the link between economic conditions and health, national economic indicators may be too broad to detect lived experiences (Catalano and Bellows 2005; Ruhm 2005). In December of 2008, county unemployment rates in the United States ranged from under 2 percent in three counties in North Dakota to 25 percent in Mackinac County, Michigan (Bureau of Labor Statistics, United States Department of Labor 2009a). The vastly different economic circumstances in which people live lead to disparate health statuses.

Demonstrating this effect in a comprehensive analysis of counties in the United States, Ezzati and colleagues (2008) found wide variation in mortality across counties between 1983 and 1999,
with some counties showing continuing declining mortality rates over the period and others reversing this trend. Further, another study reported an association between county-level unemployment, poverty, and HIV survival, which was probably due to variation in local area resources (Harrison et al. 2008).

Because these local variations meaningfully affect health, relying on the national economic data analyzed in previous research may limit apt theorizing about how economic conditions affect health. The present study compares the effect of economic change across counties, allowing us to test whether local economic conditions have the same effect as national economic conditions. Despite theoretical reasons to expect the effect of county-level economic trends to differ from those of national trends, we are persuaded by the strength of the national-level empirical evidence to hypothesize that our results will be in the same direction.

**H1:** Increasing county-level unemployment rates are associated with a trend of improving self-rated health.

**Moderating Effects: Education and Race**

If social conditions are the fundamental cause of health and illness, understanding how social factors moderate the relationship between recession and health can help build a theory about why the counterintuitive association has persisted across time. Indeed, early research proposed that labor market position would be associated with health change during recessions (e.g., Brenner 1979). While our data do not permit us to measure how individual unemployment interacts with county-level unemployment, we can assess how two social characteristics—educational attainment and race—interact with economic conditions. Because not all social groups face similar experiences when unemployment rates increase, trends by education and race may provide insight into possible theoretical mechanisms linking economic conditions and health.

The educational credentials required for many jobs have increased, often without a clear occupational need for greater education (Brown 2001). Persons with greater educational attainment are presumed to have better skills and more opportunities for internal and external job advancement. Consequently, the well-being of those with weaker education credentials may be more sensitive to economic change, while those with better credentials may be less affected by changing economic conditions. Yet, the scant research on the interaction between unemployment rates and individual educational attainment does not provide a clear picture of how education moderates the health effects of economic change. Using national data that examined individual mortality, Edwards (2008) found a weak moderating effect of education in the expected direction. Specifically, those with the least education experienced a greater mortality during recession, while those with high education experienced reduced mortality. As Edwards notes, because mortality is a rare event in a random sample of the population, large standard errors prohibit strong conclusions in this study. The present study uses a health indicator with more variation, which will improve understanding of the relationship.

**H2:** More rapidly rising county-level unemployment rates weaken the positive trend in self-rated health for those with less education compared to the trend for those with more education.

Racial groups also vary in their relationship to the labor market, as economic recessions often have a stronger negative impact on racial minorities. Unemployment statistics for December
2008 show that whites over age 25 with a high school diploma had an unemployment rate of 7.2 percent, while similar blacks had an unemployment rate of 11.8 percent. The gaps are similar among those with bachelors’ degrees, though among this group, blacks’ unemployment rate was increasing more rapidly (tabulations from Bureau of Labor Statistics 2009b). Given blacks’ disadvantaged relationship to the labor market, one might hypothesize that economic conditions more strongly affect trends in black health than white health. Contradicting this notion, Granados’ (2005) examination of U.S. mortality rates and economic conditions in the twentieth century finds no racial differences in effects. The present study will further explore the question by testing whether race moderates the effect of local unemployment conditions on health. We base our hypothesis on the expectation that disadvantage in the labor market increases the likelihood of experiencing negative consequences during economic decline.

**H3:** More rapidly rising county-level unemployment rates weaken the positive trend in self-rated health among blacks compared to the trend for whites.

### METHODS

**Data**

The primary source of data for this project is the 2008/2009 Ohio Family Health Survey (OFHS), which was sponsored by several Ohio state agencies as well as two state universities, managed by the Ohio State University Ohio Colleges of Medicine Government Resource Center and the Health Policy Institute of Ohio, and conducted by Macro International. The purpose of the OFHS is to collect data about insurance coverage, access to health care, and health status of adults and children in Ohio (Duffy and Muzzy 2009). The OFHS is a cross-sectional telephone survey, including both landlines and cell phones. The survey was in the field from August 6, 2008, until January 24, 2009, allowing us to examine trends in self-rated health during a period of rapidly rising unemployment. It included an oversample of black residents. After deleting proxy respondents (i.e., those who answered for another household member) and cases with one or more missing values on the independent variables, the final adult sample comprises 44,268 respondents. All analyses include sampling weights at the respondent level to correct for (1) unequal sampling probabilities due to the survey design; (2) differential non-response, reducing non-response bias; and (3) differences in the characteristics of the sample versus the population (Duffy and Muzzy 2009). We append several county-level measures from the 2005 to 2009 American Community Survey to the respondent-level file, described in the variables section below.

**Variables**

**Dependent variable**

Self-rated health indicates the overall physical and mental health status of respondents. Many studies of individual-level unemployment use self-rated health (Burgard, Brand, and House 2007; Ferrie et al. 2005; Kessler, House, and Turner 1987), but we are aware of no studies of macro-level unemployment in the United States that have used this measure. Self-rated health status is
an excellent assessment of overall health and predictor of future mortality (Idler and Benyamini 1997). Further, individuals adapt their rating of their health when their health status changes (e.g., following weight loss) (Rohrer et al. 2009). This makes self-rated health a good indicator of health for this study, because it is unlikely that we would find changes in diagnosed health problems immediately, such as diabetes or hypertension.

Self-rated health is usually dichotomized, often comparing fair/poor health and excellent/very good/good health. However, a recent study of several large national data sets showed that for comparisons over time, dichotomizing self-rated health into excellent versus the other categories results in more stable and reliable estimates of population health (Salomon et al. 2009). Thus, in this analysis comparisons will be made between excellent and very good/good/fair/poor health.

**Respondent-level independent variables**

The primary respondent-level independent variables of interest are education and race. For education we created dummy variables for respondents with a high school diploma or some college and a college degree or more, with less than a high school diploma as the omitted category. For race, we coded a dummy variable scored “1” for non-Hispanic white and “0” for non-Hispanic black (hereafter referred to as “white” and “black,” respectively). Other variables were also included in the analysis as control variables: income (categories representing the percentage of the federal income to needs ratio), health insurance coverage (none versus some), age, sex, and marital status. For analyses focusing on education, we treat race as a control variable. For analyses focusing on white/black inequality, we treat education as a control variable.

**County-level independent variables**

At the county-level, unemployment rates were taken from the Ohio Department of Job and Family Services website for August 2008 and January 2009 (Ohio Department of Job and Family Services 2009). The statistical models use August as the baseline level of unemployment and predict a growth rate for each county based on the unemployment rates in August and January, as shown in equation 1 (Preston, Heuveline, and Guillot 2001:12):

\[
\begin{align*}
  r_{UNEMP} &= \frac{1}{5} \ln \left( \frac{UNEMP_{01/09}}{UNEMP_{08/08}} \right) \times 100, \\
\end{align*}
\]

where \( UNEMP_{08/08} \) was the county unemployment rate in August 2008 and \( UNEMP_{01/09} \) was the equivalent rate in January 2009.

We also control for several county-level characteristics by coding the type of county (urban, suburban, rural, or Appalachian), and by appending county-level measures of percent black, percent poor, and population size (in 10,000s) from the 2005 to 2009 American Community Surveys (ACS). Since observed effects of unemployment might be spurious due to the correlation of

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2 The OFHS has a small percentage of non-white, non-black respondents, including 2.2 percent Hispanic, 1.9 percent Asian, and 1.6 percent members of other races; however, these shares were too low and spatially concentrated to support the multilevel analyses that follow. Hence, we restrict our analyses to whites and blacks.

3 The ACS replaced the decennial census “long form” in 2010. Because the ACS is a smaller survey than the decennial census, five years’ worth of ACS summary file data are needed to produce reliable estimates.
unemployment with county type and with demographic indicators, we control for these characteristics. We include an indicator for Appalachian counties because they have a distinct history and conditions—beyond simply being rural places—that appear to affect health outcomes (e.g., Smith and Holloman 2011).

Table 1 shows the distribution of the variables in the analysis. Overall, 18.4 percent of the sample reports excellent health. Most Ohioans in the sample have a high school education or some

<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>SD</th>
<th>Min.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable</strong></td>
<td></td>
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<tr>
<td>Self-reported excellent health</td>
<td>0.184</td>
<td></td>
<td>0</td>
<td>1</td>
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<tr>
<td><strong>Independent variables</strong></td>
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<tr>
<td><strong>Individual-level</strong></td>
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<tr>
<td>Education</td>
<td></td>
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<tr>
<td>Less than high school diploma</td>
<td>0.126</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>High school diploma/some college</td>
<td>0.616</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Bachelor’s degree/grad school</td>
<td>0.258</td>
<td></td>
<td>0</td>
<td>1</td>
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<tr>
<td>Race</td>
<td></td>
<td></td>
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<tr>
<td>Non-Hispanic white</td>
<td>0.886</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Non-Hispanic black</td>
<td>0.114</td>
<td></td>
<td>0</td>
<td>1</td>
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<tr>
<td>Income:needs ratio (% of national average)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt;100</td>
<td>0.150</td>
<td></td>
<td>0</td>
<td>1</td>
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<tr>
<td>101–300</td>
<td>0.393</td>
<td></td>
<td>0</td>
<td>1</td>
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<tr>
<td>&gt;300</td>
<td>0.458</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>No health insurance</td>
<td>0.130</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
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<tr>
<td>18–24</td>
<td>0.104</td>
<td></td>
<td>0</td>
<td>1</td>
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<tr>
<td>25–34</td>
<td>0.159</td>
<td></td>
<td>0</td>
<td>1</td>
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<tr>
<td>35–44</td>
<td>0.187</td>
<td></td>
<td>0</td>
<td>1</td>
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<tr>
<td>45–54</td>
<td>0.190</td>
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<tr>
<td>55–64</td>
<td>0.175</td>
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<td>65+</td>
<td>0.186</td>
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<td>1</td>
</tr>
<tr>
<td>Female</td>
<td>0.532</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Married or cohabiting</td>
<td>0.601</td>
<td></td>
<td>0</td>
<td>1</td>
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<tr>
<td><strong>County-level</strong></td>
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<tr>
<td>Unemployment rate</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>August 2008 (%)</td>
<td>7.2</td>
<td>1.3</td>
<td>4.9</td>
<td>10.3</td>
</tr>
<tr>
<td>Average change in unemployment rate (% per month)</td>
<td>8.9</td>
<td>3.2</td>
<td>0.3</td>
<td>16.1</td>
</tr>
<tr>
<td>County type</td>
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<tr>
<td>Urban</td>
<td>0.136</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Suburban</td>
<td>0.307</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Rural</td>
<td>0.557</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Appalachian</td>
<td>0.318</td>
<td></td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>2005–2009 percent black</td>
<td></td>
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<td></td>
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<tr>
<td>2005–2009 poverty rate</td>
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<td></td>
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<tr>
<td>2005–2009 population size (in 10,000)</td>
<td></td>
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</table>

*Note. Individual-level n = 44,268; county-level n = 88. Data are weighted and proxy respondents deleted from analysis.*
college (61 percent), fewer have a bachelor’s degree or more (26 percent), and fewer still have less than a high school diploma (13 percent). The average county unemployment rate in August 2008 was 7.2 percent, with a minimum of 4.9 percent and maximum of 10.3 percent. On average, county unemployment rates increased by about 8.9 percent per month, with a minimum increase of 0.3 percent and a maximum of 16.1 percent per month.

Analytic Plan

Our statistical analysis employs hierarchical linear modeling (HLM) techniques (Raudenbush and Bryk 2002). In brief, we estimate determinants of variation across counties in the average log odds of reporting excellent health (1) in August 2008 and (2) from August 2008 to January 2009. The HLM linear growth model in this case treats multiple observations of Ohio’s 88 counties as nested within those counties, yielding estimates of monthly change in the average county-level log odds of reporting excellent health. The linear growth model is appropriate because of the small number of observations (six) in each county. With more time points, it would also be desirable to model non-linear trends; however, as noted by Raudenbush and Bryk (2002:163), the linear growth model “can provide a good approximation for more complex processes that cannot be fully modeled because of the sparse number of observations.”

Although these are county-level analyses, we control for respondent-level characteristics for three distinct reasons: first, we wish to account for county-to-county variation in population composition to isolate effects of changes in county-level unemployment versus differences in the characteristics of county residents. In the language of HLM, we estimate “covariate-adjusted” intercepts (August averages) and slopes (August to January average change). Second, the OFHS interviewed different segments of the sample at different times in the roughly six-month period it was in the field. Thus, we control for fluctuations over time in the composition of the sample by estimating covariate-adjusted parameters. Finally, as noted in hypotheses 2 and 3, we are interested in differential effects of county-level unemployment on educational and racial gaps across counties.

Modeling Strategy

Level-1 models

The fullest level-1 model for our analysis of education is shown below:4

$$\ln(Ωy_{ijk}) = π_{0jk} + π_{1jk}(HS_{ijk}) + π_{2jk}(COLL_{ijk}) + \sum_{p=3}^{13} π_{pjk}(x_{pijk}) + e_{ijk}$$  \hspace{1cm} (2)

where $$ln(Ωy_{ijk})$$ is the log of the odds of person $$i$$ in month $$j$$ in county $$k$$ reporting excellent health, $$π_{0jk}$$ is the county average log odds of reporting excellent health for persons with less than a high

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4Models for our analyses of black means and white gaps can be derived by substituting an uncentered “white” dummy variable for the two education dummy variables, and then moving group-mean centered versions of the education variables into the vector of controls in equation 2.
school diploma (the omitted category for education) in month \( j \) in county \( k \), \( \pi_{1jk} \) is the average county gap in the log odds of excellent self-reported health for persons with a high school diploma or some college, relative to the omitted category, and \( \pi_{2jk} \) is the equivalent gap for persons with a college degree or greater. Finally, the \( \pi_{ijk} \) are effects of 11 control covariates, centered around their county-specific means,\(^5\) and \( e_{ijk} \) is a level-1 error term.

**Level-2 models**

The first three parameters on the right-hand side of equation (2) become outcomes to be estimated as a function of a single level-2 variable, the month in which each respondent was surveyed. Hence, the level-2 models are expressed as:

\[
\pi_{0jk} = \beta_{00k} + \beta_{01k}(MONTH_{jk}) + r_{0jk}, \quad (3a)
\]

\[
\pi_{1jk} = \beta_{10k} + \beta_{11k}(MONTH_{jk}) + r_{1jk}, \quad \text{and} \quad (3b)
\]

\[
\pi_{2jk} = \beta_{20k} + \beta_{21k}(MONTH_{jk}) + r_{2jk}. \quad (3c)
\]

By coding \( MONTH \) as 0 for August 2008, 1 for September 2008 . . . and 5 for January 2009, the intercepts in the models above refer to county-level averages in August 2008. That is, the \( \beta_{00k} \) refer to the covariate-adjusted average log odds of reporting excellent health among persons with less than a high school diploma, and the \( \beta_{10k} \) and \( \beta_{20k} \) refer to the education gaps, all in August 2008. The three \( MONTH \) slopes (the \( \beta_{p1k} \)) are, respectively, the county average per-month change from August 2008 to January 2009 in the covariate-adjusted log odds of excellent self-reported health for respondents with less than a high school diploma (eq. 3a), the average monthly change in the gap between persons with a high school diploma or some college and persons without a high school diploma (eq. 3b), and the average monthly change in the gap between persons with a college degree or greater and persons without a high school diploma (eq. 3c). These, then, are the key county-level dependent variables: a set of intercepts representing county averages in August 2008, and a set of slopes representing county-specific changes from August 2008 to January 2009.

**Level-3 models**

At level 3, these 88 sets of six parameters (i.e., one set of six for each of Ohio’s 88 counties) are predicted by county-level characteristics:

\[
\beta_{00k} = \gamma_{000} + \gamma_{001}(UNEMP_k) + \sum_{q=2}^{5} \gamma_{00q}(x_{kq}) + u_{00k}, \quad (4a)
\]

\(^5\)By “group-mean centering” these covariates, the intercepts and \( \pi_1 \) and \( \pi_2 \) parameters carry the interpretation of mean log odds and gaps in those means for persons whose other characteristics (e.g., income, marital status) are average for their county of residence.
\[ \beta_{01k} = \gamma_{00} + \gamma_{01} \left( \text{UNEMP}_k \right) + \sum_{q=2}^{5} \gamma_{01q} \left( x_{kq} \right) + u_{01k}, \] (4b)

\[ \beta_{10k} = \gamma_{100} + \gamma_{101} \left( \text{UNEMP}_k \right) + \sum_{q=2}^{5} \gamma_{10q} \left( x_{kq} \right) + u_{10k}, \] (4c)

\[ \beta_{11k} = \gamma_{110} + \gamma_{111} \left( \text{UNEMP}_k \right) + \sum_{q=2}^{5} \gamma_{11q} \left( x_{kq} \right) + u_{11k}. \] (4d)

All covariates in equations 4a to 4d are grand-mean centered, which allows the intercepts to be interpreted as averages for counties that are also average on all included county-level covariates. For example, in equation 4a, the intercept \( \gamma_{000} \) is interpreted as the overall county average log odds of reporting excellent self-rated health in August 2008 for persons with less than a high school diploma in a county that is average on all covariates included in the model. The \text{UNEMP} slope \( \gamma_{001} \) is interpreted as the “effect” of a one-percent higher county unemployment rate in August 2008. Thus, \( \gamma_{001} \) is the cross-sectional association of county unemployment rates with self-reported health for the least educated Ohioans.

Equation 4b estimates effects of changes in county-level unemployment and the four time-invariant covariates on changes in the log odds of self-reported excellent health, again for the least educated group of Ohioans. In this model, the intercept is interpreted as the overall sample average, while the \( \gamma_{010} \) parameter represents the estimated effect of a one-percent per month increase in the county unemployment rate. Equations 4c and 4d yield similar information, except that the dependent variables are not means, but rather average county-level gaps between respondents with a high school diploma or some college and those without. Equations for the gaps between those with a college degree or greater and those with less than a high school diploma are not shown, but are similar to equations 4c and 4d.

**RESULTS**

**Overall Trends**

Figure 1 presents the unadjusted percent reporting excellent health in each of the categories of the individual-level independent variables. These lines are derived from HLM random coefficients models in which no additional level-1 covariates (i.e., in addition to race or education) and no level-3 covariates were included. As such, they represent estimated linear trends over time, unadjusted for any individual- or county-level characteristics.

The solid line is the overall average over the period. Supporting our first hypothesis and past research, over the period of increasing unemployment rates we observe a slightly increasing likelihood of reporting excellent self-rated health. Panel A shows that this trend holds for all three education groups, with somewhat sharper increases for the least-educated Ohioans. Panel B shows that whites and blacks followed that same upward path, with the steeper slope for blacks.
County-level Unemployment Effects on Educational Gaps in Reporting Excellent Health

Table 2 shows the cross-level interaction effects of county-level unemployment on the respondent-level education gaps in the likelihood of reporting excellent health, when controlling for other individual-level factors. The results in Model 1 show that in August 2008, higher county-level unemployment predicts lower odds of reporting excellent health at all educational levels. The coefficient estimate of −0.224 in the top left-hand panel of Table 2

---

6The robust standard error estimates provided by the HLM software assume some kind of probability sample. We, however, analyzed repeated measures from a census of Ohio counties. Hence, the standard errors should be interpreted as “estimates of parameter dispersion contaminated by measurement error” (Grodsky and Pager 2001:552). In other words, smaller standard errors indicate more consistent effects of the independent variables on the dependent variables. Coefficients marked with an asterisk indicate that they are at least twice the size of their standard errors.
TABLE 2

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TABLE 2 (Continued)

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Note. Level-1 $n = 44,268$; level-2 $n = 528$; level-3 $n = 88$. Models include level-1 controls for race/ethnicity, health insurance, age, income, marital status, and sex. Data are weighted at level 1.

translates to an odds ratio of 0.80, meaning that Ohioans with less than a high school diploma in counties with one percent higher unemployment rates in August on average had 20 percent lower odds of reporting excellent self-rated health, compared to equivalent residents of counties with one percent lower unemployment rates in August. Expressed in terms of probabilities, for Ohioans whose other characteristics gave them the average probability of reporting excellent self-rated health (0.184, from Table 1) the slope of the line relating county-level unemployment in August to the probability of reporting excellent self-rated health is $-3.4$ percent.\(^7\)

In contrast, county-level unemployment rates in August have a weaker association with self-rated health for those with greater than a high school diploma. For both better-educated groups, the effect is about $-0.07$ ($-0.22 + 0.15$), for an odds ratio of 0.93 and a marginal effect of $-1.1$ percent (see note 7). In other words, a snapshot of conditions in August shows that unemployment rates in that month were less negatively correlated with self-rated health for those with more education, compared to those with less.

Looking at change over time, Table 2 shows that, on average, the probability of reporting excellent health was increasing over time for the least-educated Ohioans ($\gamma_{010} = 0.072$ in Model 1; also see Fig. 1). However, a larger increase in unemployment over the six-month period weakens that effect ($\gamma_{010} = -0.016$ in Model 1). One way to gauge the magnitude of this effect is to compare two hypothetical counties: one with the average rate of change in the unemployment rate and one with a one standard deviation greater rate of change (3.2 percent higher). We calculate the difference in rates of change in unemployment rates between these two hypothetical counties to be $-1.3$ percent per month.\(^8\) This effect can be seen in graphic form in Figure 2.

---

\(^7\)The marginal effect of a one-unit increase in a covariate $x_k$ in a logistic regression model is calculated as the partial derivative of $y$ with respect to $x_k$, or $\frac{\partial \Pr(y = 1|x)}{\partial x_k} = \Pr(y = 1|x)\left[1 - \Pr(y = 1|x)\right]\beta_k$. If the conditional probability of reporting excellent health = 0.184, then $0.184(1 - 0.184) - 0.224 = -0.337$, or $-3.4$ percent (Long 1997).

\(^8\)The effect of a discrete change in a covariate $x_k$ in a logistic regression model is calculated as the difference in the probability that $y = 1$ when $x_k$ differs by some value $\delta$, or $\Delta \Pr(y = 1|x) = \Pr(y = 1|x, x_k + \delta) - \Pr(y = 1|x, x_k)$. Because we grand-mean centered the $\text{rUNEMP}$ variable in Table 2 (see eq. [4b]), we can calculate the change in the probability of

Notes: Lines come from coefficients in Model 1, Table 2 and refer to a hypothetical county with the August unemployment rate and growth in the unemployment rate from August to January implied by the figure title (e.g., one SD below average).

reporting excellent health for counties that are one standard deviation greater than the mean as \( \exp(0.072 + 3.2(-0.016)) \) \( = \) 0.504 and for the average county as \( \exp(0.072) \) \( = \) 0.518. The difference between these two quantities is –1.3 percent (0.518 – 0.504 \( = \) –0.013 \times 100). See Long (1997:75-79) for details.
panel A, by comparing the slopes of the dashed lines, representing different rates of county-level unemployment change.

In contrast, increasing unemployment rates have little effect on those with a high school education or greater, as can be seen by the relatively consistent slopes of the lines in Figure 2, panels B and C. Together, these results generally support our second hypothesis. In other words, increases in county-level unemployment did not substantially affect the probability of reporting excellent health among those with a high school diploma or more; however, among those with less than a high school diploma, increasing unemployment served to flatten the overall positive trends we observe for the six-month period.

**County-level Unemployment Effects on Racial Gaps in Reporting Excellent Health**

Turning to Table 3, we find the results of the analysis of race and county-level unemployment on self-reported health. Overall, whites have better average self-rated health than blacks in the multilevel models presented in Table 3. For blacks who were average on all level-1 characteristics and lived in a county with the average August unemployment rate, their probability of reporting excellent health was 0.154. For statistically equivalent whites this probability was 0.180.9

Table 3 also presents the coefficients for the effect of changing county-level unemployment by race. Figure 3 presents the results graphically. The rate of unemployment change among blacks is the opposite of the expected effect: there is a divergence in predicted self-rated health, but those in counties with the highest rate of increasing unemployment have better self-rated health over the period (compare the dashed line with the solid line). Whites, on the other hand, show the anticipated effect in different county conditions, with more rapidly increasing county-level unemployment change predicting weaker increase in the likelihood of predicting excellent health. These results do not support the hypothesis that rapidly rising unemployment rates more negatively affect blacks compared to whites.

**DISCUSSION**

Research in the United States suggests that during poor economic times at the national level, population health improves (Chay and Greenstone 2003; Dehejia and Lleras-Muney 2004; Granados 2005; Granados and Diez-Roux 2009; Laporte 2004). Scholars have yet to develop a clear theoretical explanation for the relationship. Because the association persisted over the entire last century, social factors likely cause the unexpected association. In order to advance understanding of the relationship between economic change and health, we evaluated whether this conclusion holds when studied over a short period at the onset of a recession, with local economic indicators, and across race and educational attainment. Overall, our results support past research showing that economic downturn is associated with better health. At the same time, our analysis of the effect of education and race produced some unexpected results that offer ideas about the mechanisms responsible for the counterintuitive association between economic cycles and health.

---

9For blacks: $\Pr(y = 1) = \frac{\exp(\gamma_{00} + \gamma_{100})}{1 + \exp(\gamma_{00} + \gamma_{100})} = \frac{\exp(-1.705)}{1 + \exp(-1.705)} = 0.154$;

For whites: $\frac{\exp(\gamma_{00} + \gamma_{100})}{1 + \exp(\gamma_{00} + \gamma_{100})} = \frac{\exp(-1.705 + 0.186)}{1 + \exp(-1.705 + 0.186)} = 0.180$. 

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### TABLE 3


<table>
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<th>Parameter estimate</th>
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**Note.** Level-1 \(n = 44,268\); level-2 \(n = 528\); level-3 \(n = 88\). Models include level-1 controls for education, health insurance, age, income, marital status, and sex. Data are weighted at level 1.
Before assessing the effect of changing county-level unemployment on health, we examined a snapshot of the relationship between county unemployment and health. In the month of August, before the recession began, higher county-level unemployment rates were associated with decreased likelihood of excellent health. These results reflect other research that finds that poor local economic conditions are related to diminished health (e.g., Ezzati et al. 2008; Harrison et al. 2008).

Despite this association at one time point, we find that declining economic county-level conditions are associated with a trend toward improved health status. Thus, the present study supports the findings of past research by showing that the counterintuitive relationship exists even at the local level. By showing opposing cross-sectional and trend effects—higher cross-sectional unemployment associated with poorer average health, while a trend of increasing unemployment is associated with improving health—our data present the paradox of the relationship between economic trends and health with local area data.
Other results provide clues about the nature and causes of the relationship. Our use of a self-assessed, subjective health indicator over a short time period results speak to the issue of timing, whether there is a lag between economic change and change in health. The change in average self-rated health in this study, during a short period that experienced the initial dramatic rise in unemployment rates, provides more evidence that health effects are not lagged from the beginning of a recession. Rather, as economic conditions change, individuals’ perceptions of their health simultaneously change, a finding that suggests potential mechanisms for the relationship. Previous research has suggested that environmental factors that fluctuate with economic cycles cause mortality changes. While the evidence for this causal effect is convincing, it is unlikely to be the complete explanation. Recent changes in environmental conditions are unlikely to be observed and influence self-rated health, especially in the very short term. Economic conditions are more easily observed by individuals and are more widely reported in the media. Thus, an alternative possibility is that social forces lead to changes in health during economic recessions and booms. We speculate about specific social and psychological effects below as we discuss the how education and race affect the association between changing unemployment rates and health.

We hypothesized that people with less advantageous positions in the labor market, here operationalized as less educational attainment and black race, would suffer negative health consequences during a time of rising unemployment. With education, we found support for this notion. The rate of county-level unemployment change had little effect on those with a college degree or more. In contrast, among those with less than a high school diploma, the rate of change in the county unemployment rate more strongly affected trends in health. Specifically, below average increases in unemployment were associated with more rapidly improving average health among those with the least education. Thus, similar to Edwards’ (2008) study, there was weak support for the hypothesis that resources provided by more education protect individuals during an economic downturn.

Turning to race, we did not find support for the proposition that white race provides health benefits in places where unemployment is rising rapidly. For whites, the most positive health trajectory was in locations with the most slowly rising unemployment rates. In contrast, blacks showed an effect in the opposite direction; the strongest trend toward improved self-rated health was observed in counties with the most rapid rises in unemployment rates. While the effects were small, the study period was a brief six months.

Taken together, the results in this paper present a complicated, and sometimes contradictory, picture. Nonetheless, we can use the results to suggest possible mechanisms linking the economy and health. Above all, the results suggest that social processes are responsible for the association between economic change and health. The immediacy of the effect suggests a social psychological effect. That the counterintuitive effect persists at the local level provides additional clues to the mechanisms and further suggests a social and/or social psychological effect.

The moderating effects of education and race offer unexpectedly contradictory theoretical pathways. Education appears to buffer against the effects of recession. Traditional theories of the effect of social inequality on health predict this relationship. Greater social capital and economic capital (e.g., unmeasured wealth) provide both tangible health-protective goods and services and protect against stress that less advantaged people may face during an economic downturn. While this widely-accepted theoretical perspective offers guidance for the effect of education on health
during a time of rapidly rising unemployment, it does not elucidate the relationship between race, local unemployment conditions, and health.

The unanticipated effect for blacks does lead to interesting routes for future studies. Blacks’ relationship to the labor market may provide one potential explanation for the trend toward more rapid improvement in health in places with the most negative unemployment trends. Blacks’ weaker position in the labor market, during good times and recessions, may help account for the unexpected pattern during a period of rapidly rising county unemployment. Past research has found that self-rated health is linked to relative deprivation, independent of real income (Subramanyam et al. 2009; Zheng 2009). Perhaps blacks in high unemployment counties evaluate their situation, and their health, more favorably than blacks in low unemployment counties. It is possible that this effect offers a clue to the broader, unexpected relationship between unemployment rates and health in other studies. Perhaps because even during a recession most people are not unemployed or facing extreme financial circumstances (e.g., home foreclosure), people evaluate their life circumstances more favorably. Future research should investigate whether the metric for evaluation of well-being changes during a recession. The effect of a social force on individuals’ perceptions of their well-being could provide insight into the mechanisms linking the economy and health status.

Another possible route for future research is the assessment of one’s standing relative one’s own employment history. Turner (1995) found that psychological distress was lowest among those persons who were previously unemployed, but currently employed, in high unemployment regions. This combines both a relative personal and contextual assessment of well-being. Perhaps relative assessment helps to explain the surprising effect for blacks, who are more likely to have been unemployed in the past. Our results, along with previous empirical research, suggest that attention to the interaction between individual-level and contextual-level variables may be a key to uncovering the mechanisms linking the economy and health status.

With the perspective that broad social forces affect health, one might wonder whether Obama’s election during the survey period affected the results. In another article, we (Malat, Timberlake, and Williams 2011) evaluate the effect of Obama’s success on the self-rated health of whites, blacks, and Hispanics. We find a brief positive effect after the Democratic National Convention, but no evidence for an “Obama effect” on self-rated health over the entire interval.

There are some limitations to the findings presented in this article. First, the analyses were not able to assess how individual unemployment interacts with county-level unemployment. Individual employment data were not collected for many of the cases, so we did not include it in these analyses. Second, self-rated health is a generally considered a stable measure that would not respond easily to changes in the broader social, or economic, environment. Yet, we did find that self-rated health changed over the period, suggesting sensitivity in the measure. Because much remains to be learned about the relationship between economic change and health, researchers must learn what they can from available datasets. That the cross-sectional analyses of the effect of unemployment, education, and race all produce the expected results supports use of the dataset for our investigation. And as we have shown, this article contributes to the literature on unemployment change on trends in health despite data limitations.

The theoretically surprising relationship between economic change and health requires more research to uncover the conditions in which the relationship holds. The present article contributes to this work by showing that this effect holds with county-level unemployment data, and at the
very beginning of a recession. The effect is moderated by education and race in surprising ways that suggest needed future studies on how social factors link economic cycles and health.

ABOUT THE AUTHORS

Jennifer Malat is Associate Professor of Sociology at the University of Cincinnati. Her primary research areas are medical sociology and racial inequality, with a focus on racial inequality in health care. Her recent work assesses how macro-level social forces affect health.

Jeffrey M. Timberlake is Associate Professor of Sociology at the University of Cincinnati. His research focuses on the sociology of population, community and urban sociology, racial and ethnic relations, and quantitative research methods. Research projects focus on the causes and consequences of urban inequality, particularly racial and ethnic residential segregation.

REFERENCES


