UHERO
THE ECONOMIC RESEARCH ORGANIZATION
AT THE UNIVERSITY OF HAWAIʻI

# Health and Health Inequality during the Great Recession: Evidence from the PSID

by

Chenggang Wang, Huixia Wang, and Timothy J. Halliday

Working Paper No. 2017-7R
October 4, 2017

UNIVERSITY OF HAWAIʻI AT MANOA
2424 MAILE WAY, ROOM 540 • HONOLULU, HAWAIʻI 96822
WWW.UHERO.HAWAII.EDU

**Health and Health Inequality during the Great Recession: Evidence from the PSID***

Chenggang Wang
University of Hawaii at Manoa, Department of Economics

Huixia Wang
Hunan University, School of Economics and Trade

Timothy J. Halliday+
University of Hawaii at Manoa, Department of Economics
University of Hawaii Economic Research Organization
IZA

First Version: July 6, 2016
Last Update: October 3, 2017

## Abstract

We estimate the impact of the Great Recession of 2007-2009 on health outcomes in the United States. We show that a one percentage point increase in the unemployment rate resulted in a 7.8-8.8 percent increase in reports of poor health. In addition, mental health was adversely impacted. These effects were concentrated among those with strong labor force attachments. Whites, the less educated, and women were the most impacted demographic groups.

Keywords: Great Recession, Health Behaviors, Health Outcomes, Inequality

JEL Classification: I0, I12, I14

---

* We thank participants at the IZA Workshop on the Social and Welfare Consequences of Unemployment in Bonn, Germany and the 2017 SOLE Meetings in Raleigh, North Carolina for useful feedback. In addition, we thank Susan Averett, an associate editor at this journal, and five anonymous referees for invaluable comments. All errors are our own.
+ Corresponding author. Address: 2424 Maile Way; 533 Saunders Hall; Honolulu, HI 96822. E-mail: halliday@hawaii.edu

## I. Introduction

Recessions are a major source of systematic risk to households. Because they affect large groups of people at once, they are very difficult to insure. Moreover, due to moral hazard problems, public insurance schemes like unemployment insurance only provide limited recourse to the unemployed. As a consequence, recessions can have serious, adverse impacts on household and individual welfare.

One of the more commonly studied of these potential impacts is the effect of recessions on human health. Early work on the topic indicated that poor macroeconomic conditions raised mortality rates substantially (*e.g.* Brenner 1979). However, seminal work by Ruhm (2000) pointed out severe methodological shortcomings in this earlier work and he showed that, once these issues are corrected, mortality rates tend to *decline* during recessions so that mortality rates are actually pro-cyclical in the aggregate data.[1] Improved health-related behaviors due to relaxed time constraints and tightened budget constraints was cited by Ruhm (2000, 2005) as a mechanism driving these results, although subsequent work by Stevens, *et al.* (2015) suggested that higher rates of vehicular accidents and poor nursing home staffing during robust economic times were the primary mechanisms. Notably, more recent work by Ruhm (2015) has shown that mortality rates for many causes of death did not decline during the Great Recession and that mortality due to accidental poisoning actually increased. Other recent work by Crost and Friedson (2017) shows, in aggregate data, that mortality rates increase with the unemployment rate when both are calculated by education group. All of these studies utilize aggregate state-level mortality and unemployment rates and so their unit of analysis is a state/time observation.

On the other hand, studies that are based on individual-level data mostly show that health and health-related behaviors worsen during recessions. For example, Gerdtham and Johannesson (2003, 2005) use micro-data and show that mortality risks increase during recessions for working-aged men. Similar evidence over the period 1984-1993 is provided for the United

[1] This result has been replicated in other countries such as Canada (Ariizumi and Schirle 2012), France (Buchmueller, *et al*. 2007), OECD countries (Gerdtham and Ruhm 2006), Spain (Tapia Granados 2005), Germany (Neumayer 2004), and Mexico (Gonzalez and Quast 2011).

States by Halliday (2014) who used the Panel Study of Income Dynamics (PSID). Browning and Heinesen (2012) use Danish administrative data and show that involuntary job displacement has large effects on mortality, particularly, from cardiovascular disease which is similar to results in Halliday (2014).[2] In a similar vein to these studies, Jensen and Richter (2003) showed that pensioners who were adversely affected by a large-scale macroeconomic crisis in Russia in 1996 were five percent more likely to die within two years of the crisis. Related, Charles and DeCicca (2008) use the National Health Interview Survey (NHIS) and MSA-level unemployment rates to show that increases in the unemployment rate were accompanied by worse mental health and increases in obesity. Hence, while the macro-based studies tend to be somewhat conflicted, the micro-based studies indicate that the uninsured risks posed by recessions have real, adverse impacts on human health. That said, there are some micro-based studies that show that health improves during recession *e.g.* Ruhm (2003) who uses a sample from the NHIS from 1972-1981.

In this study, we consider how the Great Recession impacted the health of Americans. Specifically, we ask three questions. First, did the Great Recession impact health in the United States? Second, how did it impact health? Third, who did it impact?

This study offers several innovations to the existing literature. First, we estimate the relationship between the Great Recession and health at the individual level rather than the state level. We contend that this is more appropriate since as has been shown by Arthi, *et al.* (2017) and argued by Halliday (2014), migration can severely bias aggregate health measurements such as mortality rates. This may underscore why studies at the aggregate level either find positive or, on occasion *e.g.* Ruhm (2015), null results, whereas studies at the individual level typically find negative effects, although Ruhm (2003) is an exception. Second, in contrast to many other studies that use individual level data, we do not rely on epidemiological surveillance data sources such as the Behavioral Risk Factor Surveillance System (BRFSS) or the NHIS which may have more sample variability from year-to-year due non-response than the PSID. Third, we employ granular information on economic conditions at the county-level whereas many other studies that employ

[2] Browning and Heinesen (2012) builds on earlier work by Browning, Dano, and Heinesen (2006) that does not find any impact of displacements on hospitalization by using more outcomes including mortality, a sample with stronger labor force attachments, as well as a substantially larger data set.

individual level data are conducted at the state level. The main benefit of doing this is that county-level indicators necessarily have more geographic variation than state-level indicators which results in more precise estimates. Fourth, like Lindo (2015) does in an aggregate context, we are able to investigate how using economic indicators at different levels of aggregation affects our results albeit in the context of an analysis at the individual level. Fifth, we compare how our estimates differ if we employ the unemployment rate or the employment/population (E/P) ratio. As far as we can tell, this has not been done by any other studies that employ individual-level data. Sixth, because we investigate the impact of the Great Recession on different demographic subgroups, we provide additional detail about how the recession widened or narrowed important health inequalities.

The Great Recession is an important episode to study since this recession was the deepest and longest recession during the post-war period. In fact, Farber (2015) estimates that, over this period, one in six workers lost their job at least once. From trough to peak, the unemployment rate increased from 4.6 to 9.3 percent which is the largest increase during the post-war period. In addition, unemployment duration during the Great Recession was, by far, the longest of any recession since World War II peaking at just over 40 weeks.

Aside from being the deepest recession in the post war period, another reason to focus on the Great Recession is that some important work suggests that the relationship between recessions and health may have changed during the most recent recession. For example and as already discussed, Ruhm (2015) shows that the relationship between state-level unemployment and mortality rates has been severely dampened during the past ten years, although deaths due to accidental poisoning did increase. These are the deaths that Case and Deaton (2015) often refer to as “deaths of despair” which have been increasing over the past 15 years among whites with low levels of education.

There some important papers that have investigated how the Great Recession impacted well-being. In one paper, Deaton (2012) investigates how a rich set of subjective measures of well-being collected by Gallup responded to various events during the recession period. One of the main findings of this work is that many of these indicators track the stock market surprisingly well which the author suggests might be due to the well-being measures and the stock market responding to the same news events during this period. Another recent study that considers the health impact of the Great Recession is Tekin, *et al.* (2013). They use the BRFSS and find little impact of the Great Recession on health outcomes using state-level unemployment rates. This is the study from the literature that is closest to our own.

Our study offers two innovations upon the Tekin, *et al.* (2013) study. First, because we employ panel data from the PSID, we have a reliably consistent sample across years and are not subject to the notoriously high non-response rates in many epidemiological surveillance data sources. For example, during the 2000's, the NHIS had a non-response rate over ten percent (p. 44, Massey and Tourangeau 2012) and the BRFSS had a non-response rate approaching 50 percent during the same period (p. 188, Groves, *et al.* 2009). If the non-response in these surveys is in any way correlated with the business cycles or employment status, then researchers employing these data sources will have biased results. The second advantage of our study is that we are able to employ more granular information on economic conditions at the county level using the PSID's geocode file. This provides us with a more detailed portrait of the economic conditions that an individual faces. It also provides us with more variation in our right hand side variables which increases the precision of our estimates and, hence, the power of our study.

There are also some other studies that have investigated the impact of the Great Recession on inputs to health, particularly, illicit drug use. For example, Carpenter, *et al.* (2017) look at the impact of the business cycle over the period 2002-2013 on illicit drug use in the United States and find that there is strong evidence that economic downturns lead to increases in the use of prescription pain relievers. This result is consistent with findings in Ruhm (2015) who showed that mortality due to accidental poisoning in the United States increased during the Great Recession. Related, Bassols, *et al.* (2016) showed that the Great Recession increased legal and illegal drug use in Spain. Pabilonia (2015) investigates the impact of the Great Recession on teenagers' risky behaviors in the Youth Risk Behavior Survey and the American Time Use

Survey.  Argys, *et al.* (2016) show that the run-up of household debt during the Great Recession was accompanied by increased mortality risk.   Finally, Asgeirsdottir, *et al.* (2012) and Asgeirsdottir, *et al.* (2016) showed that the 2008 economic crisis in Iceland reduced consumption of health compromising goods.

The findings of our study are as follows.  First, there is very strong evidence that the Great Recession impacted the health of working-age Americans.  Using a common omnibus measure of health status, self-reported health, we show that a one percentage point increase in the unemployment rate resulted in a 7.8-8.8 percent increase in reports of fair or poor health status.  This finding is robust to a number of tests.  These effects were not present in a sample of older people with weaker labor force attachments.  Second, the Great Recession adversely impacted mental health and increased heavy drinking, although these effects were weaker than the impact on self-rated health.  Third, we detect the strongest impacts on mental and physical health for white Americans and those with at most 12 years of schooling.  In addition, women were impacted more than men.  In this sense our results are consistent with important findings by Case and Deaton (2015) who show that mortality rates of whites with less education have increased during the past 15 years.

The balance of this paper is organized as follows.  In the next section, we discuss some avenues through which the macro-economy can affect health.  After that, we discuss our data.  After that, we describe our empirical methods.  We then present our findings.  Finally, we conclude.

## II. Mechanisms

Theoretically, the impact of recessions on health and health-related behavior is ambiguous.  On the whole, the health-promoting effects of recessions will happen via time investment in health and reduced consumption of vices provided that they are normal goods.  On the other hand, the harmful effects of recessions will happen through increased consumption of vices if they are inferior goods or increased stress levels.

### Health-promoting Effects

These effects have been discussed by many including Ruhm (2000). Essentially, recessions will reduce the opportunity cost of time and incomes. As a consequence, time investment in health will increase and consumption of vices that are also normal goods will decline. Ruhm (2005) does provide evidence for both of these channels using the BRFSS. Evidence for reduced consumption of alcohol and other potentially harmful goods is also provided by Asgeirsdottir, *et al.* (2012) and Cotti, *et al*. (2015). However, it is important to bear in mind that alcohol is a normal good and, so just because some drinking declines during recessions that does not preclude problematic binge drinking from increasing.

Harmful Effects

Recessions may damage health via several channels. First, if some vices are inferior goods, then consumption of them will increase. Moreover, although it may be the case that a good such as alcohol is normal (*e.g.* Cotti, *et al*. (2015)), excessive use of it might be an inferior good if it is used as a coping mechanism during stressful times (*e.g.* Dee (2001), Davalos, *et al.* (2012), Paling and Castello (2017)). A similar argument can be made for obesity since food can also provide comfort during stressful times. Second and related, the stress associated with job loss or the threat of it may, by itself, be a risk factor for a number of ailments which could, thus, lead to a deterioration of health status. A third possible mechanism is that people might have less medical coverage during recessions.

## III. Data

We utilize data from the PSID which is a national longitudinal study that collects individual-specific information on health, demographic, and socioeconomic outcomes that is run by the University of Michigan. The PSID began in 1968 with interviews of about 5000 families and has continued to interview their descendants since then. To obtain county-specific information, we use the county identifier or the geocode file from the PSID.[4] We utilize the 2003, 2005, 2007, 2009, 2011 and 2013 waves. The 2003 and 2005 waves correspond to the pre-recession period;

[4] See http://simba.isr.umich.edu/restricted/ProcessReq.aspx for details.

the 2007 and 2009 waves correspond to the recession period; and the 2011 and 2013 waves correspond to the recovery period. Because only heads of household and their spouses were asked the health-related questions in the survey, we limit our sample to them. We employ regional economic indicators from the Local Area Unemployment Statistics (LAUS) of the Bureau of Labor Statistics (BLS) which were then merged into the PSID for each year using the PSID's geocode file.

For most of the estimations, we restrict the sample to people with strong labor force attachments which we essentially define to be people between ages 25 and 55 and in the labor force. Sample sizes by year for the working aged sample are reported in Table A1. Specifically, we restrict the working age sample by dropping people who reported being out of the labor force, retired and disabled people, students, and housewives. We also present some estimates for people age 65 or older. The idea of using this sample is that this sub-sample has weaker labor force attachments and so if the impact of the recession on health is operating through the labor market then we should see attenuated effects in this population.[5] In addition, because the goal of this exercise is to see if the recession impacted people with weak labor force attachments, we included retired and disabled people, students (to the extent that there are full-time students older than 65), and housewives, as well as people who reported being out of the labor force.

Descriptive statistics for our sample are reported in Table 1a for people ages 25-55 and Table 1b for people 65 and older. The data can be categorized under the rubrics: economic conditions, health outcomes, and demographic controls. The demographic variables are fairly self-explanatory and are listed in the bottom portion of the table.

Health Outcomes

The health outcomes that we consider are drinking, mental health, self-reported health status (SRHS), and obesity. The drinking variable that we use is an indicator for heavy drinking. We

[5] We concede that people older than 65 should not be completely unaffected by the business cycle. However, we still contend that they should be less affected than people in their prime working years.

follow the Centers for Disease Control and Prevention's definition and define heavy drinking to be 15 or more drinks per week for men and eight or more drinks per week for women. We use the K6 Non-specific Psychological Distress Scale as an indicator for mental health which was also used by Charles and DeCicca (2008). The K6 index is based on six questions designed to measure different markers of psychological distress including reports of feelings of effortlessness, hopelessness, restlessness, sadness, and worthlessness during the past 30 days. The K6 distress scale is a weighted sum of these six outcomes. Kessler, *et al.* (2003) has shown that the K6 scale is at least as effective as a number of other depression scales in predicting serious mental health problems. Next, SRHS is a categorical variable that takes on integer values between one and five where one is excellent and five is poor. We transform the SRHS variable into a binary variable that we call poor health when SRHS equal to four or five. Halliday (2014) has shown that SRHS is strongly predictive of mortality in the PSID. Finally, obesity is an indicator for body mass index exceeding 30 which is the standard definition from the Centers for Disease Control and Prevention.

Our obesity variable warrants some discussion. As discussed by Cawley, *et al*. (2015), there is a large degree of measurement error in measures of BMI based on self-reported height and weight due to misreporting. To address this, we employ a procedure from Cawley (2004).[6] Specifically, we used measures of actual and reported height and weight from the National Health and Nutrition Examination Survey (NHANES). We then regressed actual outcomes on a quadratic in their reported values for different gender/race cells. We then used these estimates to predict actual height and weight in the PSID using the estimates from the NHANES and based our obesity calculations off of these predictions. Using this procedure, we calculate that 36 percent of our sample of 25-55 years olds is obese. The most comparable number from Cawley, *et al.* (2015) is 33.52 percent but corresponds to a sample of people ages 20-64 (see Table 2 of that paper).

[6] A more recent and probably better procedure is discussed by Courtemanche, *et al.* (2015). However, implementing this procedure would have required estimating a fairly non-parametric regression function in the NHANES relating actual and reported height and weight and then taking these estimates to the PSID to predict actual height and weight which would have been a bit more cumbersome than using the procedure from Cawley (2004).

Given that SRHS plays a central role in this paper, some words concerning the quality of this variable should be mentioned. It is true that these data can be criticized for being subjective. However, Smith (2003), Baker, *et al.* (2004), and Halliday (2014) have shown that it is highly correlated with both morbidity and mortality. In addition, Bound (1991) has shown that SRHS is highly predictive of retirement even when adjusting other confounding variables. Given this, we contend that SRHS is a good proxy for underlying health status.

Economic Indicators

We employ data on regional unemployment rates and E/P ratios. These were obtained from the LAUS of the BLS and were merged into the PSID using its geocode file either by county or by state. Note that for the E/P ratios, the employment counts in the numerators come from the LAUS and the population counts in the denominators come from the Surveillance, Epidemiology, and End Results Program (SEER). In total, we had 3218 counties in our data.

In our sample of working age adults, the average county-level unemployment rate was 6.95 percent with a standard deviation of 2.75. At the state level, the corresponding statistics are 6.88 and 2.20 percent. As indicated by the standard deviations, there is 25 percent more variation at the county level than at the state level.[7]

The average county-level E/P ratio was 0.56 with a standard deviation of 0.09. At the state level, the corresponding statistics are 0.60 and 0.04. Accordingly, there is 125 percent more variation at the county level. Note that there is substantially more county-level variation in the E/P ratios than in the unemployment rates.[8]

County Population Sizes

---

[7] A regression of the county-level unemployment rate onto county fixed effects has an $R^2$ of 47.55 percent indicating that over half of the variation of the county-level unemployment rate is within counties which is critical for our research design's success.
[8] The $R^2$ from a regression of the E/P ratio onto a set of county dummies is 41.72 percent once again indicating substantial within county variation in the county-level E/P ratios.

In Table A2, we report some descriptive statistics on county population sizes from the merged PSID-LAUS-SEER data set as well as from the raw SEER data. The average county size in the merged data is 99,555, but the median is 35,341 indicating that the distribution of county sizes is skewed to the right. This is reflected in a high standard deviation of 160,419. In the raw data, the mean is lower, 94,997; the percentiles are also uniformly smaller than in the merged data set. This indicates that the PSID tended to sample from larger counties. In Figure A1, we present a kernel density estimate of the county sizes also from the merged data set. As suggested by the descriptive statistics, the distribution of county sizes is skewed to the right.

Attrition and Non-Response

Based on our reading of the literature, we do not believe that attrition in the PSID has a similar impact as non-response in the NHIS or, especially, the BRFSS on estimates of the effect of recessions on health. While it is not well-understood how non-response varies over the business cycle in either of these surveys, it is known that, even after adjustments are made for non-response in the BRFSS, key sociodemographic factors in the BRFSS differ from the census (Schneider, *et al.* 2012). In addition, Barrett-Connor, *et al.* (2011) concludes on p. 67 that, "Because it typically does not collect locally representative survey samples, the BRFSS has limited use for local-level analyses and research. Such research is necessary to support efforts to address geographic and social disparities. The CDC recognized the need for local data and used aggregated BRFSS data to produce a limited set of annual estimates for local geographic areas, but these vary from year to year due to sampling variations." On the other hand, work by Fitzgerald (2011) concludes that the PSID sample weights do an admirable of preserving the representativeness of the PSID despite some attrition. In addition, Fitzgerald, *et al.* (1998) conclude that conditioning on a rich set of covariates in many models of key socioeconomic outcomes results in little impact of attrition on parameter estimates.

There does appear to be a somewhat weak relationship between the business cycle and attrition in the PSID with attrition probabilities lowering when the economy worsens. In the appendix, Table A3, we report results from a regression of an indicator for attriting in the next survey year on the county level unemployment rate and a battery of exogenous controls both with county fixed effects. This is the same specification that we discuss in greater detail in the next section. We estimate one specification without and one with state-specific trends. In the specification without the trends, we see that a one percentage point increase in the unemployment rate is associated with a 0.4 percentage point decline in the attrition probability and this estimate is significant at the ten percent level. In the next column when we include state trends, the estimate falls to -0.002 but is no longer significant. Finally, note that in our main sample of people ages 25-55, the probability of attriting the next survey year (two years hence) is about 11 percent; this corresponds to an annual attrition probability of 5.6 percent which is substantially lower than the non-response rates in either the NHIS or the BRFSS. So, while attrition may not be trivial in the PSID, it does not appear to be systematically related to the business cycle once we properly adjust the regressions.

## IV. Methodology

To estimate the effect of the Great Recession on health outcomes and health-related behaviors, we employ a linear regression model. If we let *i* denote the individual, *c* the county, *s* the state, and *y* the year, the basic estimation model is:

$$H_{icsy} = \beta_0 + \beta_1 U_{cy} + \beta_2 X_{iy} + \delta_c + \delta_y + \delta_s * t + \varepsilon_{icsy}. \qquad (1)$$

The dependent variable, $H_{icsy}$, is a health outcome or behavior. The county-specific (or state-specific) unemployment rate (or E/P ratio) in a given year is denoted by $U_{cy}$. The vector, $X_{iy}$, contains individual-specific control variables including age, gender, race, marital status, and education. We also include county and year dummies which are denoted by $\delta_c$ and $\delta_y$. Finally, we include state-specific time trends which are denoted by $\delta_s * t$. We estimate two different specifications of equation (1) both with and without the state-specific trends which has the advantage of controlling for confounding within state trends but the disadvantage of eliminating potentially meaningful exogenous variation in the county-level economic indicators. All standard errors were clustered on the county level. Finally, we employ the weights provided by the PSID when estimating these models.[9]

Choosing the Economic Indicator

There are two important choices that must be made with respect to the economic indicator on the right-hand side of the estimation equation. The first is whether to focus on state- or county-level indicators. The second is whether to use the E/P ratio or the unemployment rate. We argue that the most appropriate choice in our context is the county-level unemployment rate. Consequently, we mostly focus on these in this paper. However, we do present results at the state and county levels using both indicators.

There are pros and cons of focusing the analysis at the state versus the county level. One advantage of using county-specific indicators is that within states, there can be considerable variation in local economic conditions, particularly, in larger states. As such, using county-specific indicators may do a better job of capturing the macroeconomic circumstances that an individual is facing. In this sense, state-specific indicators can be viewed as error-ridden proxies for the county-specific indicator. Another argument in favor of county-specific rates is more quotidian, which is that there simply is more variation in county-level indicators than at the state-level which increases the precision of estimates based on them.

On the other hand, Bartick (1996) and Hoynes (2000) point out that there can be considerable amounts of measurement errors in county-specific unemployment rates since these come from surveys and imputations are often used for small counties. Another argument against using indicators at the county level comes from Lindo (2015). He argues that spillovers in regional economic conditions across counties may result in smaller estimates at the county level.

To shed light on spillovers in our context, we provide a formal test for their presence. To do this, we compute an F-test of the equality of the coefficients on the county and state unemployment

[9] Note that there is some controversy surrounding when and when not to weight regressions (see Deaton (1997) and Solon, *et al*. (2015)). Our main reason for employing the weights is per the recommendation of Fitzgerald, *et al.* (1998) as a remedy for sample attrition in the PSID.

rates.  First, we estimated two models, one with the county unemployment rate and one with the state unemployment rate, as a system of seemingly unrelated regressions.  This allowed us to compute the covariance between the two parameter estimates.  Next, using the two estimates from this system, we tested the null that the two parameters from the different equations were equal.  This provides a formal test of the presence of spillovers that properly accounts for a positive covariance in the two estimates.

Next, it has been argued that county-level E/P ratios may be preferred to county-level unemployment rates because the former come from administrative data sources, whereas the unemployment rates come from either surveys or imputations (in the case of smaller counties).  It is true that the numerators of the E/P ratios come from administrative sources so should be less prone to measurement errors.  However, because population counts only come every census year, the denominators do rely on imputations within census years for county and state populations. Moreover and in contrast to the county-level unemployment rates which only use imputations for smaller counties, the E/P ratios necessarily must rely on imputed denominators for all counties and states between census years.  So, it is not accurate to say that the E/P ratios are free of measurement errors.  Like the regional unemployment rates, they are also measured with errors.[10]

In this paper, we focus on results that employ the county-level unemployment rate for the following reasons.  First, as the reader will see, we provide no evidence of spillovers in our context.  Second and as we already discussed, there is considerably more variation in the county-level indicators than in the state-level indicators, specifically, 25 percent more for the unemployment rate and 125 percent more for the E/P ratio.  This implies that we will have more precise estimates at the county level than at the state level.  Third and related, it is not necessarily the case that there is less measurement error in the E/P ratios.  The fact that the county-level E/P ratios have a standard deviation that is 125 percent higher than at the state level is consistent with the notion that there is more measurement error in the county-level E/P ratio than in the

[10] That said the unemployment rate is not free of limitations.  For example, due to the discouraged worker effect, people may drop out of the labor force which would impact the denominator.

unemployment rates.

Controlling for Heterogeneity

Our study also does a comprehensive job of controlling for heterogeneity across local labor markets relative to previous studies in this literature. Importantly, Tekin, *et al.* (2013) and Ruhm (2003) only control for state fixed effects and trends which only accounts for state-level confounders. Clearly, the use of state fixed effects may be too coarse since potential confounders such as education and health infrastructure, culture, demographic composition, and weather may vary at a finer geographical level.

We also adopt a more comprehensive approach to addressing heterogeneity by including individual fixed effects which subsume the county fixed effects. This approach has the advantage of controlling for a greater amount of unobserved confounding variables than the county fixed effects. However, it comes with the cost of wasting important exogenous variation in the data as has been argued by Deaton (1997) and Angrist and Pischke (2008). It is also less efficient and exacerbates the attenuation bias caused by measurement errors (*e.g.* Griliches and Hausman 1986). As such, we view the results with the individual fixed effects as a robustness check for our core results and we primarily focus on the results with the county fixed effects for most of the paper.

## V. Results

In this section, we answer our three research questions. First, did the Great Recession affect health? Second, how did it affect health? Third, who did it affect?

*Did the Great Recession affect health?*

To address this question, we estimate equation (1) using poor health as the dependent variable. We begin with the SRHS measure as it is a good omnibus measure of health status that exhibits meaningful time series variation. Moreover and as previously mentioned, it is highly correlated with mortality in the PSID.  The results are reported in Table 2a.

Our core results are reported in the first four columns.  In the first column where county fixed effects are included, the estimate is 0.008 and is significant at the one percent level.  This indicates that a one percentage point (PP) increase in the unemployment rate results in a 0.8 PP increase in the probability of reporting poor health.  Inclusion of state-specific trends slightly attenuates the estimate to 0.007 but it is still highly significant.  The mean of reports of poor health in our data is 0.09, so these estimates constitute a 7.8-8.8 percent increase.  One concern with the estimates with the county fixed effects in the first two columns is that healthier people may selectively migrate out of depressed areas as shown in Halliday (2007).  If this were to happen then areas with high unemployment rates would have a less healthy population due to selection as opposed to a structural effect of the macroeconomy on individual health.  One way to address this is with the inclusion of individual fixed effects as in columns three and four. Another way to address this is to re-estimate the models in the first two columns for a subsample of people who do not move counties while in the sample.  These results are reported in columns three through six.  All four estimates estimates are between 0.007 and 0.008 and remain significant at the one percent level.  This indicates that selective migration is not driving our results.

In columns seven and eight, we use the state unemployment rate instead of the county unemployment rate.  The estimates are 0.010 and 0.009 without and with state-specific trends. While this is larger than the analogous estimates in the first two columns, the magnitude of the difference is not as large as what was found in Lindo (2015).  The p-values on an F-test of the equality of the coefficients on the county and state unemployment rates are close to unity indicating that we cannot reject the null that the two estimates are the same.  This casts doubt that there are spillover effects in our context.

It is important to point out that these estimates are actually quite different from a corresponding estimate in Tekin, et al (2013) of 0.001 from Table 2.[11]  Hence, our estimates are actually about

[11] Note that Tekin, *et al* (2013) do not report their unemployment rates as percentages.

eight times larger. This is interesting because our estimates from the PSID that use state-level unemployment rates are close to estimates that use county-level unemployment rates (also from the PSID). This suggests that there may be something about the BRFSS that is driving the difference in the two sets of estimates, as opposed to the level of aggregation of the right-hand side variable.

We also report estimates based on county and state level E/P ratios in the final four columns. Of these four estimates, only the estimate using the state-level ratio in column 11 is significant. It is interesting to note that the estimates that use the state E/P ratios are substantially larger than those that use the county-level ratios. One possible reason for this is that the estimated county populations in the denominators are more inaccurate than the state population estimates which could result in more measurement error at the county level. In addition, none of the corresponding estimates with the other health outcomes produced a significant estimate; these results are reported in the appendix in Table A4. Given that most of our effects appear to be operating through the county-level unemployment rate, we will focus on it for the duration of the paper.

Finally, we estimate the same models as in Table 2a except that we drop observations that reside in small counties. Specifically, we estimate the models for people living in counties with populations above the $15^{th}$ percentile in the merged data. We do this since the BLS imputed unemployment rates for smaller counties. In addition, given our discussion about the denominators in the E/P ratios, there may be reasons to believe that measurement errors in these indicators are greater in smaller counties.

The results are reported in Table 2b and are basically identical to those in Table 2a except some of the standard errors are slightly larger due to dropping 15 percent of the observations. If measurement errors were more problematic in smaller counties, then we would expect to see larger estimates in this table than in the previous table (provided that we are dealing with well-behaved classical measurement error). That said, this does not mean that measurement errors are not a problem, overall. It just means that they do not appear to be more important in smaller counties than in larger counties.

*How did the Great Recession affect health?*

Having established that the Great Recession impacted an omnibus health measurement, we now try and understanding how the recession impacted different components of health. To accomplish this, we estimate the model in equation (1) using the K6 index, the heavy drinking indicator, and the obesity indicator as the dependent variables.

The results are reported in Table 3. First and consistent with Tefft (2011), we see in the first two columns that mental health as proxied by the K6 scale deteriorated during the Great Recession. The estimates without and with the state-specific trends are significant at the ten percent level. Note that in columns three and four where we use state-level unemployment rates, both estimates are slightly smaller in magnitude and not significant, but we cannot reject that these estimates are equal to the estimates at the county level. Once again, we cannot reject the null that there are no spillovers. Moving on to drinking in columns one and two of the next panel, we see that a one PP increase in the county-level unemployment rate increases the propensity to drink by 0.2-0.5 PP, but neither estimate is significant at conventional levels. The corresponding estimates with the state unemployment rate in columns seven and eight are similar in magnitude, although neither of these estimates is significant at conventional levels. Once again, we do not find any evidence of spillovers. Finally, we look at obesity in the final four columns and see no evidence of any effects.

Next, in Table 4, we estimate our model for our four main outcomes on a sample that is 65 or older that has weak labor force attachments. None of the estimates are significant. Although it is true that due to a smaller sample size, this may be the result of less power. However, it is interesting to note that the magnitudes also tend to be smaller than the corresponding magnitudes in Tables 2 and 3 for the working age population, so the lack of significance is not only due to higher standard errors. This is suggestive that our effects are operating via the labor market.

*Who was impacted the most by the Great Recession?*

Finally, we investigate how the Great Recession affected different socioeconomic groups. In Table 5, we estimate our models separately for blacks and whites. In Table 6, we estimate the model separately for high school and college educated people. Finally, in Table 7, we estimate the models separately by gender.

In Table 5, we report the results for blacks in the top panel and for whites in the bottom panel. For blacks, we do not see any impacts on poor health or the K6 scale. In contrast, we do see strong evidence of effects on these outcomes for whites. Based on the two outcomes which we view as good proxies for physical and mental health, the recession had larger effects on whites. Next, looking at drinking, we actually see stronger evidence for the recession impacting the drinking behavior of black Americans than white Americans. The estimates for blacks indicate that a one PP in the unemployment rate is associated with a 1.1-1.7 PP increase in the propensity for heavy drinking and both estimates are significant at the ten percent level. The corresponding estimates of whites are not significant and are smaller in magnitude.

Finally, looking at obesity in column seven which excludes the state-trends, there is evidence of impacts on obesity albeit in opposing ways. A one PP increase in the unemployment rate increases the propensity to be obese for blacks by 1.1 PP but *decreases* the propensity for whites by 0.6 PP. However, these results are not robust to the inclusion of state-trends in the final column. These conflicting effects on obesity warrant further investigation in another paper.

Our interpretation of the results stratified by race is that there is stronger evidence that the recession impacted the mental and physical health of white Americans than black Americans. This is consistent with recent findings by Case and Deaton (2015) who provide evidence of increased mortality rates for less educated whites over the period 1999-2013 and Falconi, *et al*. (2016) who show that there was an increased risk of death from stroke for non-Hispanic white men over the period 2000-2010 in California. However, it is a puzzle that there is evidence that the recession appeared to increase drinking and obesity, which we view as inputs into the production of health, for black Americans but that this did not manifest in any observable health consequences as proxied by SRHS and the K6 index.

Table 6 is analogous to the previous table except that now we stratify by education level. First, we see that none of the estimates are significant for college graduates. Second, we see that, for the high school educated, there are significant impacts on SRHS in both columns one and two. Third, the point-estimates for the effects on drinking are substantially larger for the high school educated than for the college educated, but they are not significant at conventional levels. On the whole, this table suggests that there is stronger evidence that the recession had larger impacts on the less educated.

Finally, in Table 7, we investigate gender differences in the effects of the Great Recession on health. First, we see substantially larger impacts on SRHS for women than for men. The point estimates for women are 0.010 and 0.007 without and with the state-specific trends. Both are significant at the one percent level. The corresponding estimates for men are 0.004 and 0.005 and neither is tightly estimated. Next, we see that the point-estimates when drinking is the dependent variable are higher for men than for women, but once again they are only marginally significant. Interestingly and similar to white Americans, there is also some weak evidence that obesity rates for women declined as a consequence of the recession.

**VI. Conclusions**

In this paper, we showed that the Great Recession resulted in worse health outcomes. We built on previous work by employing more granular information on local macroeconomic conditions by using the geocode file from the Panel Study of Income Dynamics. Specifically, we showed that a one percentage point increase in the unemployment rate results in a 7.8-8.8 percent increase in reports of poor health. In addition, increases in unemployment are also associated with worse mental health and increases in heavy drinking for black Americans. The bulk of the effects on physical and mental health were borne by whites, the less educated, and (to a lesser extent) women. This is consistent with important recent findings by Case and Deaton (2015) who show that mortality of less educated whites has risen over the period 1999-2013.

Our work departs from other work that uses individual-level data to investigate how health is impacted by the business cycle in important ways. First, we do not rely on epidemiological surveillance data that has notoriously high non-response response. This is especially true of the BRFSS that can have non-response rates approaching 50 percent. Second, we employ granular information on macroeconomic conditions at the county-level. While our point-estimates when looking at the impact of the unemployment rate on self-rated health are very similar when we use unemployment at both the county and state levels, the estimates that are based on the county-level rates have much smaller standard errors since there is more variation at the county-level than at the state-level. Note that work by Tekin, *et al.* (2013) that uses the BRFSS and state-level variation delivers quantitatively different point-estimates that are also very imprecise. Finally, our work shows no evidence of spillovers in the PSID which is a contrast to studies at the aggregate level.

Another important point is that our findings are not consistent with most of the aggregate studies in this literature in that we do not find compelling evidence that any of our health measures improved during the Great Recession aside from some weak evidence that obesity rates declines for whites and for women. It is important to note that at the aggregate level the effects of recessions on health tend be positive or more recently null, whereas, at the individual level, they tend to be negative. Indeed, our results are consistent with a growing body of evidence that employs individual-level data and shows that health tends to deteriorate when the economy worsens.

## References

Angrist, Joshua D., and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton university press, 2009.

Argys, Laura M., Andrew Friedson, and M. Melinda Pitts. "Killer Debt: The Impact of Debt on Mortality." (2016).

Ariizumi, Hideki, and Tammy Schirle. "Are Recessions Really Good for your Health? Evidence from Canada." *Social Science & Medicine* 74, no. 8 (2012): 1224-1231.

Arthi, Vellore, Brian Beach, and W. Walker Hanlon. *Estimating the Recession-Mortality Relationship when Migration Matters*. No. w23507. National Bureau of Economic Research, 2017.

Ásgeirsdóttir, Tinna Laufey, Hope Corman, Kelly Noonan, and Nancy E. Reichman. "Lifecycle effects of a recession on health behaviors: Boom, bust, and recovery in Iceland." *Economics & Human Biology* 20 (2016): 90-107.

Asgeirsdottir, Tinna Laufey, Hope Corman, Kelly Noonan, Þórhildur Ólafsdóttir, and Nancy E. Reichman. *Are recessions good for your health behaviors? Impacts of the economic crisis in Iceland*. No. w18233. National Bureau of Economic Research, 2012.

Baker, Michael, Mark Stabile, and Catherine Deri. "What do self-reported, objective, measures of health measure?." *Journal of Human Resources* 39, no. 4 (2004): 1067-1093.

Barrett-Connor, Elizabeth, J. Z. Ayanian, E. R. Brown, D. B. Coultas, C. K. Francis, R. J. Goldberg, L. O. Gostin, T. E. Kottke, E. T. Lee, and D. M. Mannino. "A Nationwide Framework for Surveillance of Cardiovascular and Chronic Lung Diseases." *Washington DC, USA* (2011).

Bartik, Timothy J. "The Distributional Effects of Local Labor Demand and Industrial Mix: Estimates using Individual Panel Data." *Journal of Urban Economics* 40, no. 2 (1996): 150-178.

Bassols, Nicolau Martin, and Judit Vall Castelló. "Effects of the Great Recession on Drugs Consumption in Spain." *Economics & Human Biology* 22 (2016): 103-116.

Brenner, M. Harvey. "Mortality and the National Economy: A review, and the Experience of England and Wales, 1936-76." *The Lancet* 314, no. 8142 (1979): 568-573.

Bound, John. “Self-reported versus objective measures of health in retirement models,” *Journal of Human Resources* 26 (1991), 106-138.

Browning, Martin, Anne Moller Dano, and Eskil Heinesen. "Job Displacement and Stress-related Health Outcomes." *Health Economics* 15, no. 10 (2006): 1061-1075.

Browning, Martin, and Eskil Heinesen. "Effect of Job Loss due to Plant Closure on Mortality and Hospitalization." *Journal of Health Economics* 31, no. 4 (2012): 599-616.

Buchmueller, Thomas C., Michel Grignon, Florence Jusot, and Marc Perronnin. *Unemployment and Mortality in France, 1982-2002*. Centre for Health Economics and Policy Analysis, McMaster University, 2007.

Carpenter, Christopher S., Chandler B. McClellan, and Daniel I. Rees. "Economic conditions, illicit drug use, and substance use disorders in the United States." *Journal of Health Economics* 52 (2017): 63-73.

Case, Anne, and Angus Deaton. "Rising Morbidity and Mortality in Midlife among White Non-Hispanic Americans in the 21st century." *Proceedings of the National Academy of Sciences* 112, no. 49 (2015): 15078-15083.

Cawley, John. "The impact of obesity on wages." *Journal of Human resources* 39, no. 2 (2004): 451-474.

Cawley, John, Johanna Catherine Maclean, Mette Hammer, and Neil Wintfeld. "Reporting error in weight and its implications for bias in economic models." *Economics & Human Biology* 19 (2015): 27-44.

Charles, Kerwin Kofi, and Philip DeCicca. "Local Labor Market Fluctuations and Health: Is there a Connection and for whom?." *Journal of Health Economics* 27, no. 6 (2008): 1532-1550.

Cotti, Chad, Richard A. Dunn, and Nathan Tefft. "The Great Recession and Consumer Demand for Alcohol: A Dynamic Panel-Data Analysis of US Households." *American Journal of Health Economics* (2015).

Courtemanche, Charles, Joshua C. Pinkston, and Jay Stewart. "Adjusting body mass for measurement error with invalid validation data." *Economics & Human Biology* 19 (2015): 275-293.

Crost, Benjamin, and Andrew Friedson. "Recessions and health revisited: New findings for working age adults." *Economics & Human Biology* (2017).

Dávalos, María E., Hai Fang, and Michael T. French. "Easing the Pain of an Economic Downturn: Macroeconomic Conditions and Excessive Alcohol Consumption." *Health Economics* 21, no. 11 (2012): 1318-1335.

Deaton, Angus. *The Analysis of Household Surveys: a Microeconometric Approach to Development Policy*. World Bank Publications, 1997.

Deaton, Angus. "The financial crisis and the well-being of Americans: 2011 OEP Hicks Lecture." *Oxford economic papers* 64, no. 1 (2011): 1-26.

Dee, Thomas S. "Alcohol Abuse and Economic Conditions: Evidence from Repeated Cross-sections of Individual-level Data." *Health Economics* 10, no. 3 (2001): 257-270.

Falconi, April, Alison Gemmill, Deborah Karasek, Julia Goodman, Beth Anderson, Murray Lee, Benjamin Bellows, and Ralph Catalano. "Stroke-attributable death among older persons during the great recession." *Economics & Human Biology* 21 (2016): 56-63.

Farber, Henry S. *Job loss in the Great Recession and its aftermath: US evidence from the displaced workers survey*. No. w21216. National Bureau of Economic Research, 2015.

Fitzgerald, John M. "Attrition in models of intergenerational links using the PSID with extensions to health and to sibling models." *The BE journal of economic analysis & policy* 11, no. 3 (2011).

Fitzgerald, John, Peter Gottschalk, and Robert Moffitt. "The impact of attrition in the Panel Study of Income Dynamics on intergenerational analysis." *Journal of Human Resources* 33 (1998): 300-344.

Gerdtham, Ulf-G., and Magnus Johannesson. "A Note on the Effect of Unemployment on Mortality." *Journal of Health Economics* 22, no. 3 (2003): 505-518.

Gerdtham, Ulf-G., and Magnus Johannesson. "Business Cycles and Mortality: Results from Swedish Microdata." *Social Science & Medicine* 60, no. 1 (2005): 205-218.

Gerdtham, Ulf-G., and Christopher J. Ruhm. "Deaths Rise in Good Economic Times: Evidence from the OECD." *Economics & Human Biology* 4, no. 3 (2006): 298-316.

Gonzalez, Fidel, and Troy Quast. "Macroeconomic Changes and Mortality in Mexico." *Empirical Economics* 40, no. 2 (2011): 305-319.

Granados, José A. Tapia. "Recessions and Mortality in Spain, 1980–1997." *European Journal of Population* 21, no. 4 (2005): 393-422.

Griliches, Zvi, and Jerry A. Hausman. "Errors in Variables in Panel Data." *Journal of Econometrics* 31, no. 1 (1986): 93-118.

Groves, Robert M., Floyd J. Fowler Jr, Mick P. Couper, James M. Lepkowski, Eleanor Singer, and Roger Tourangeau. *Survey methodology*. Vol. 561. John Wiley & Sons, 2011.

Halliday, Timothy J. "Business Cycles, Migration and Health." *Social Science & Medicine* 64 (2007): 1420-1424.

Halliday, Timothy J. "Unemployment and Mortality: Evidence from the PSID." *Social Science & Medicine* 113 (2014): 15-22.

Hoynes, Hilary Williamson. "Local Labor Markets and Welfare Spells: Do Demand Conditions Matter?." *Review of Economics and Statistics* 82, no. 3 (2000): 351-368.

Jensen, Robert T., and Kaspar Richter. "The Health Implications of Social Security Failure: Evidence from the Russian Pension Crisis." *Journal of Public Economics* 88, no. 1 (2004): 209-236.

Kessler, Ronald C., Gavin Andrews, Lisa J. Colpe, Eva Hiripi, Daniel K. Mroczek, S-LT Normand, Ellen E. Walters, and Alan M. Zaslavsky. "Short Screening Scales to Monitor Population Prevalences and Trends in Non-specific Psychological Distress." *Psychological Medicine* 32, no. 06 (2002): 959-976.

Lindo, Jason M. "Aggregation and the Estimated Effects of Economic Conditions on Health." *Journal of Health Economics* 40 (2015): 83-96.

Massey, Douglas S., and Roger Tourangeau. *The nonresponse challenge to surveys and statistics*. Sage, 2012.

Neumayer, Eric. "Recessions Lower (Some) Mortality Rates: Evidence from Germany." *Social Science & Medicine* 58, no. 6 (2004): 1037-1047.

Pabilonia, Sabrina Wulff. "Teenagers' Risky Health Behaviors and Time Use during the Great Recession." *Review of Economics of the Household* (2015): 1-20.

Paling, Thomas, and Judit Vall Castello. "Business cycle impacts on substance use of adolescents: a multi-country analysis." *Economics & Human Biology* 27 (2017): 1-11.

Ruhm, C. J. “Are Recessions Good for Your Health?” *Quarterly Journal of Economics*, 115, no. 2 (2000): 617-650

Ruhm, Christopher J. "Good Times Make You Sick." *Journal of Health Economics* 22, no. 4 (2003): 637-658.

Ruhm, Christopher J. "Healthy Living in Hard Times." *Journal of Health Economics* 24, no. 2 (2005): 341-363.

Ruhm, Christopher J. "Recessions, Healthy No More?." *Journal of Health Economics* 42 (2015): 17-28.

Schneider, Karen L., Melissa A. Clark, William Rakowski, and Kate L. Lapane. "Evaluating the impact of non-response bias in the Behavioral Risk Factor Surveillance System (BRFSS)." *J Epidemiol Community Health* 66, no. 4 (2012): 290-295.

Smith, James P. “Health and SES over the Life-course,” unpublished mimeo (2003).

Solon, Gary, Steven J. Haider, and Jeffrey M. Wooldridge. "What are we weighting for?." *Journal of Human resources* 50, no. 2 (2015): 301-316.

Stevens, Ann H., Douglas L. Miller, Marianne E. Page, and Mateusz Filipski. "The Best of Times, the Worst of Times: Understanding Pro-cyclical Mortality." *American Economic Journal: Economic Policy* 7, no. 4 (2015): 279-311.

Tefft, Nathan. "Insights on Unemployment, Unemployment Insurance, and Mental Health." *Journal of Health Economics* 30, no. 2 (2011): 258-264.

Tekin, Erdal, Chandler McClellan, and Karen Jean Minyard. *Health and Health Behaviors during the Worst of Times: Evidence from the Great Recession*. No. w19234. National Bureau of Economic Research, 2013.

**Figure A1: Kernel Density of County Populations**

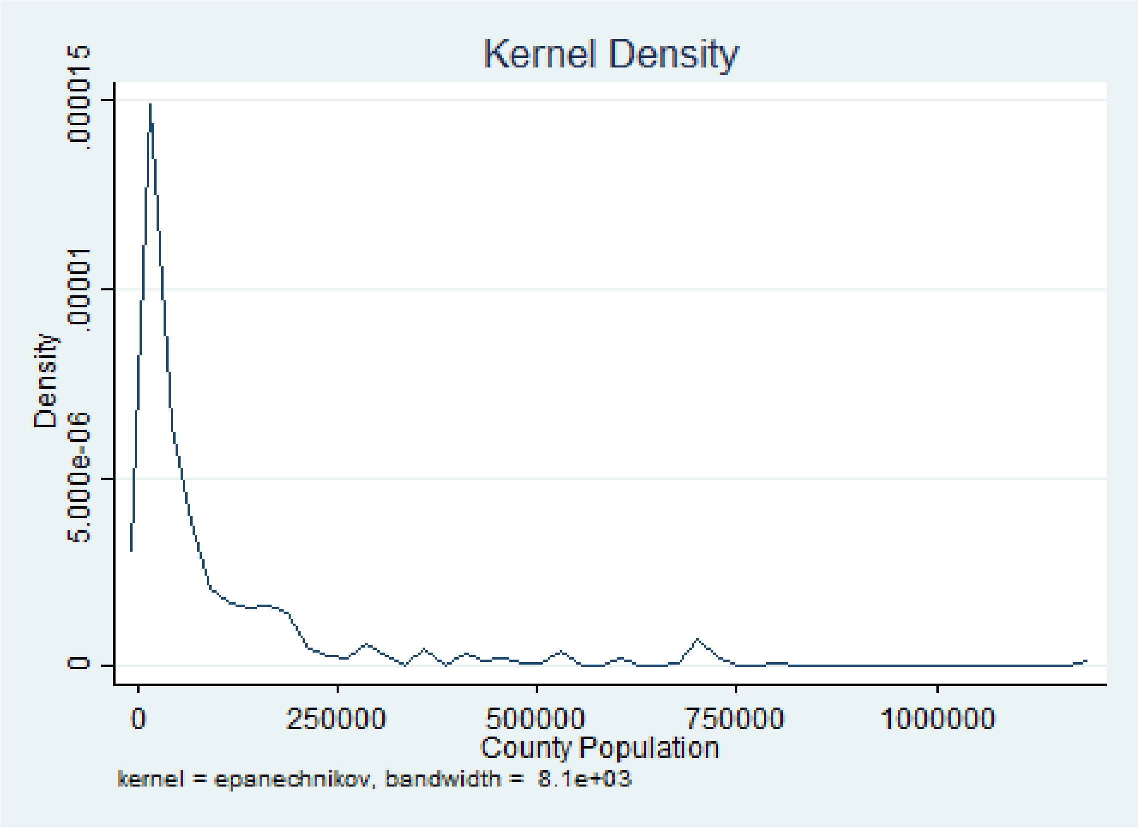

Table 1a: Descriptive Statistics, Ages 25-55

| | Obs | Mean | Std. Dev. |
|---|---|---|---|
| ***Economic Conditions*** | | | |
| County Employment to Population Ratio | 43280 | 0.56 | 0.09 |
| State Employment to Population Ratio | 43280 | 0.60 | 0.04 |
| County Unemployment Rate(%) | 43240 | 6.95 | 2.75 |
| State Unemployment Rate (%) | 43280 | 6.88 | 2.20 |
| ***Health Outcomes*** | | | |
| Heavy Drinking | 42842 | 0.27 | 0.44 |
| K6 Index | 35739 | 2.98 | 3.50 |
| Poor Health | 42964 | 0.09 | 0.28 |
| Obesity | 39402 | 0.36 | 0.48 |
| ***Demographic Controls*** | | | |
| Age | 43280 | 40.88 | 8.84 |
| Sex | 43280 | 0.52 | 0.50 |
| Married | 43275 | 0.67 | 0.47 |
| Never married | 43275 | 0.16 | 0.37 |
| Widowed | 43275 | 0.01 | 0.10 |
| Divorced | 43275 | 0.13 | 0.34 |
| Less than High School | 41205 | 0.07 | 0.26 |
| High School Graduated | 41205 | 0.32 | 0.47 |
| College | 41205 | 0.61 | 0.49 |
| White | 42608 | 0.80 | 0.40 |
| Black | 42608 | 0.13 | 0.33 |

Table 1b: Descriptive Statistics, Ages 65+

| | Obs | Mean | Std. Dev. |
|---|---|---|---|
| ***Economic Conditions*** | | | |
| County Employment to Population Ratio | 9185 | 0.56 | 0.09 |
| State Employment to Population Ratio | 9185 | 0.59 | 0.04 |
| County Unemployment Rate(%) | 9177 | 7.04 | 2.64 |
| State Unemployment Rate (%) | 9185 | 6.99 | 2.18 |
| ***Health Outcomes*** | | | |
| Heavy Drinking | 9144 | 0.06 | 0.25 |
| K6 Index | 7138 | 2.60 | 3.57 |
| Poor Health | 9060 | 0.32 | 0.47 |
| Obesity | 8401 | 0.31 | 0.46 |
| ***Demographic Controls*** | | | |
| Age | 9176 | 75.25 | 7.60 |
| Sex | 9185 | 0.43 | 0.50 |
| Married | 9185 | 0.54 | 0.50 |
| Never married | 9185 | 0.02 | 0.15 |
| Widowed | 9185 | 0.33 | 0.47 |
| Divorced | 9185 | 0.10 | 0.30 |
| Less than High School | 8635 | 0.18 | 0.38 |
| High School Graduated | 8635 | 0.40 | 0.49 |
| College | 8635 | 0.42 | 0.49 |
| White | 9030 | 0.87 | 0.33 |
| Black | 9030 | 0.08 | 0.27 |

Table 2a: Poor Health (SRHS = 4 or 5), Ages 25-55

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Unemployment Rate (County) | 0.008*** (0.002) | 0.007*** (0.002) | 0.007*** (0.002) | 0.008*** (0.003) | 0.007*** (0.002) | 0.007*** (0.003) |
| Unemployment Rate (State) | | | | | | |
| Emp/Pop Ratio (County) | | | | | | |
| Emp/Pop Ratio (State) | | | | | | |
| F-Test | | | | | | |
| County FE | X | X | | | X | X |
| Individual FE | | | X | X | | |
| State-specific Trends | | X | | X | | X |
| Non-mover Sample | | | | | X | X |
| NT | 40,721 | 40,721 | 40,721 | 40,721 | 25,142 | 25,142 |

* sig. at 10% level  ** sig. at 5% level  *** sig. at 1% level

Notes: All standard errors are clustered at the county level and are reported in parentheses. All specifications control for the demographic variables listed in Table 1 as well as year fixed effects. We report the p-value for the F-tests in brackets.

Table 2a (continued): Poor Health (SRHS = 4 or 5), Ages 25-55

| | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|
| Unemployment Rate (County) | | | | | | |
| Unemployment Rate (State) | 0.010*** | 0.009*** | | | | |
| | (0.002) | (0.003) | | | | |
| Emp/Pop Ratio (County) | | | 0.028 | 0.004 | | |
| | | | (0.030) | (0.030) | | |
| Emp/Pop Ratio (State) | | | | | -0.575** | -0.433 |
| | | | | | (0.212) | (0.289) |
| F-Test | (1)=(7) | (2)=(8) | | | (9)=(11) | (10)=(12) |
| | [0.984] | [0.995] | | | [0.976] | [0.995] |
| County FE | X | X | X | X | X | X |
| Individual FE | | | | | | |
| State-specific Trends | | X | | X | | X |
| Non-mover Sample | | | | | | |
| NT | 40,761 | 40,761 | 40,761 | 40,761 | 40,761 | 40,761 |

Table 2b: Poor Health (SRHS = 4 or 5), Ages 25-55, Dropping Small Counties (Bottom 15%)

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Unemployment Rate | 0.008*** | 0.007*** | 0.008*** | 0.008*** | 0.009*** | 0.007*** |
| (County) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) |
| Unemployment Rate (State) | | | | | | |
| Emp/Pop Ratio (County) | | | | | | |
| Emp/Pop Ratio (State) | | | | | | |
| F-Test | | | | | | |
| County FE | X | X | | | X | X |
| Individual FE | | | X | X | | |
| State-specific Trends | | X | | X | | X |
| Non-mover Sample | | | | | X | X |
| NT | 34,651 | 34,651 | 34,651 | 34,651 | 17,394 | 17,394 |

* sig. at 10% level  ** sig. at 5% level  *** sig. at 1% level

Notes: Per Table 2a.

Table 2b (continued): Poor Health (SRHS = 4 or 5), Ages 25-55, Dropping Small Counties (Bottom 15%)

| | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|
| Unemployment Rate (County) | | | | | | |
| Unemployment Rate (State) | 0.010***<br>(0.003) | 0.008***<br>(0.003) | | | | |
| Emp/Pop Ratio (County) | | | 0.034<br>(0.041) | -0.005<br>(0.045) | | |
| Emp/Pop Ratio (State) | | | | | -0.596**<br>(0.254) | -0.659*<br>(0.393) |
| F-Test | (1)=(7)<br>[0.984] | (2)=(8)<br>[0.995] | | | (9)=(11)<br>[0.976] | (10)=(12)<br>[0.995] |
| County FE | X | X | X | X | X | X |
| Individual FE | | | | | | |
| State-specific Trends | | X | | X | | X |
| Non-mover Sample | | | | | | |
| NT | 34,691 | 34,691 | 34,691 | 34,691 | 34,691 | 34,691 |

Table 3: Mental Health, Drinking, and Obesity, Ages 25-55

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | K6 Depression Index | | |
| Unemployment Rate | 0.053* | 0.057* | | |
| (County) | (0.028) | (0.030) | | |
| Unemployment Rate | | | 0.042 | 0.046 |
| (State) | | | (0.031) | (0.039) |
| F-Test | | | (1)=(3) | (2)=(4) |
| | | | [0.999] | [0.999] |
| NT | 33,937 | 33,937 | 33,937 | 33,937 |
| | | Heavy Drinking | | |
| Unemployment Rate | 0.002 | 0.005 | | |
| (County) | (0.003) | (0.003) | | |
| Unemployment Rate | | | 0.001 | 0.005 |
| (State) | | | (0.004) | (0.004) |
| F-Test | | | (1)=(3) | (2)=(4) |
| | | | [0.999] | [1.000] |
| NT | 40,364 | 40,364 | 40,404 | 40,404 |
| | | Obesity | | |
| Unemployment Rate | -0.003 | -0.002 | | |
| (County) | (0.003) | (0.003) | | |
| Unemployment Rate | | | -0.003 | 0.002 |
| (State) | | | (0.003) | (0.004) |
| F-Test | | | (1)=(3) | (2)=(4) |
| | | | [0.999] | [0.999] |
| NT | 37,609 | 37,609 | 37,647 | 37,647 |
| County FE | X | X | X | X |
| State-specific Trends | | X | | X |

* sig. at 10% level ** sig. at 5% level *** sig. at 1% level
Notes: Per Table 2a.

Table 4: Ages 65 and older

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Poor Health | | K6 Index | | Heavy Drinking | | Obesity | |
| Unemployment Rate | -0.003 | -0.002 | 0.012 | 0.022 | 0.002 | 0.001 | -0.004 | -0.006 |
| (County) | (0.005) | (0.005) | (0.049) | (0.052) | (0.003) | (0.003) | (0.004) | (0.005) |
| | | | | | | | | |
| County Fixed Effects | X | X | X | X | X | X | X | X |
| State-specific Trends | | X | | X | | X | | X |
| NT | 8,556 | 8,556 | 6,722 | 6,722 | 8,534 | 8,534 | 8,010 | 8,010 |

* sig. at 10% level  ** sig. at 5% level  *** sig. at 1% level
Notes: Per Table 2a.

Table 5: Effects by Race, Ages 25-55

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Blacks | | | |
| | Poor Health | | K6 Depression Index | |
| Unemployment Rate | 0.003 | -0.001 | -0.047 | -0.025 |
| (County) | (0.006) | (0.006) | (0.073) | (0.087) |
| NT | 12,929 | 12,929 | 10,795 | 10,795 |
| | Whites | | | |
| County Unemployment | 0.008*** | 0.007*** | 0.061** | 0.069** |
| Rate | (0.002) | (0.002) | (0.030) | (0.033) |
| NT | 25,538 | 25,538 | 21,238 | 21,238 |
| County Fixed Effects | X | X | X | X |
| State-specific Trends | | X | | X |

* sig. at 10% level  ** sig. at 5% level  *** sig. at 1% level

Notes: Per Table 2a.

Table 5 (continued): Effects by Race, Ages 25-55

| | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| | Blacks | | | |
| | Heavy Drinking | | Obesity | |
| Unemployment Rate | 0.011* | 0.017** | 0.011* | 0.006 |
| (County) | (0.006) | (0.007) | (0.007) | (0.006) |
| NT | 12,793 | 12,793 | 12,673 | 12,673 |
| | Whites | | | |
| County Unemployment | 0.000 | 0.001 | -0.006* | -0.004 |
| Rate | (0.003) | (0.004) | (0.003) | (0.003) |
| NT | 25,333 | 25,333 | 24,936 | 24,936 |
| County Fixed Effects | X | X | X | X |
| State-specific Trends | | X | | X |

Table 6: Effects by Education, Ages 25-55

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | High School Education (at most 12 years of schooling) | | | |
| | Poor Health | | K6 Depression Index | |
| Unemployment Rate (County) | 0.008** | 0.007* | 0.048 | 0.034 |
| | (0.004) | (0.004) | (0.041) | (0.045) |
| NT | 15,977 | 15,977 | 13,073 | 13,073 |
| | College Graduates | | | |
| County Unemployment Rate | 0.004 | 0.002 | 0.019 | 0.041 |
| | (0.003) | (0.003) | (0.042) | (0.048) |
| NT | 12,205 | 12,205 | 10,430 | 10,430 |
| County Fixed Effects | X | X | X | X |
| State-specific Trends | | X | | X |

* sig. at 10% level  ** sig. at 5% level  *** sig. at 1% level

Notes: Per Table 2a.

Table 6 (continued): Effects by Education, Ages 25-55

| | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| | High School Education (at most 12 years of schooling) | | | |
| | Heavy Drinking | | Obesity | |
| Unemployment Rate (County) | 0.006 | 0.009 | -0.006 | -0.006 |
| | (0.005) | (0.006) | (0.005) | (0.005) |
| NT | 15,758 | 15,758 | 14,875 | 14,875 |
| | College Graduates | | | |
| County Unemployment Rate | -0.002 | -0.001 | -0.006 | -0.003 |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| NT | 12,170 | 12,170 | 11,300 | 11,300 |
| County Fixed Effects | X | X | X | X |
| State-specific Trends | | X | | X |

Table 7: Effects by Gender, Ages 25-55

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Men | | | |
| | Poor Health | | K6 Depression Index | |
| Unemployment Rate | 0.004 | 0.005* | 0.058* | 0.050 |
| (County) | (0.002) | (0.003) | (0.032) | (0.035) |
| NT | 20,560 | 20,560 | 17,093 | 17,093 |
| | Women | | | |
| County Unemployment | 0.010*** | 0.007** | 0.043 | 0.052 |
| Rate | (0.003) | (0.003) | (0.040) | (0.044) |
| NT | 20,161 | 20,161 | 16,844 | 16,844 |
| County Fixed Effects | X | X | X | X |
| State-specific Trends | | X | | X |

* sig. at 10% level ** sig. at 5% level *** sig. at 1% level

Notes: Per Table 2a.

Table 7 (continued): Effects by Gender, Ages 25-55

| | (5) | (6) | (7) | (8) |
|---|---|---|---|---|
| | Men | | | |
| | Heavy Drinking | | Obesity | |
| Unemployment Rate | 0.005 | 0.006 | 0.002 | 0.001 |
| (County) | (0.004) | (0.004) | (0.004) | (0.004) |
| NT | 20,255 | 20,255 | 19,164 | 19,164 |
| | Women | | | |
| County Unemployment | 0.001 | 0.005 | -0.010** | -0.006 |
| Rate | (0.004) | (0.004) | (0.004) | (0.004) |
| NT | 20,109 | 20,109 | 18,445 | 18,445 |
| County Fixed Effects | X | X | X | X |
| State-specific Trends | | X | | X |

Table A1: Sample Sizes by Year, Ages 25-55

| **Year** | **Sample size** |
|---|---|
| 2003 | 7166 |
| 2005 | 7168 |
| 2007 | 7210 |
| 2009 | 7405 |
| 2011 | 7253 |
| 2013 | 7336 |

Table A2: Descriptive Statistics on County Populations

| | Merged Data | Raw SEER Data |
|---|---|---|
| Mean | 99555 | 94997 |
| Standard Deviation | 160419 | 306053 |
| $10^{th}$ Percentile | 7003 | 5215 |
| $25^{th}$ Percentile | 14976 | 11131 |
| $50^{th}$ Percentile | 35341 | 25388 |
| $75^{th}$ Percentile | 117498 | 64835 |
| $90^{th}$ Percentile | 227014 | 188947 |

Table A3: Business Cycles and Attrition, Ages 25-55

| | (1) | (2) |
|---|---|---|
| Unemployment Rate (County) | -0.004* | -0.002 |
| | (0.002) | (0.002) |
| Age | 0.005*** | 0.005*** |
| | (0.000) | (0.000) |
| Male | -0.006* | -0.006 |
| | (0.004) | (0.004) |
| Married | -0.023 | -0.023* |
| | (0.014) | (0.014) |
| Never Married | 0.003 | 0.003 |
| | (0.015) | (0.015) |
| Widowed | 0.028 | 0.027 |
| | (0.029) | (0.029) |
| Divorced | -0.024 | -0.024 |
| | (0.015) | (0.015) |
| Less than high school | 0.023*** | 0.024*** |
| | (0.009) | (0.009) |
| High school | 0.014*** | 0.014*** |
| | (0.005) | (0.005) |
| White | -0.007 | -0.007 |
| | (0.006) | (0.006) |
| County Fixed Effects | X | X |
| State-specific trends | | X |
| NT | 40,771 | 40,771 |

* sig. at 10% level  ** sig. at 5% level  *** sig. at 1% level

Notes: Per Table 2a.

Table A4: Mental Health, Drinking, and Obesity, E/P Ratios, Ages 25-55

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | | K6 Depression Index | | |
| Unemployment Rate | 0.535 | 0.619 | | |
| (County) | (0.399) | (0.455) | | |
| Unemployment Rate | | | -0.552 | -3.286 |
| (State) | | | (2.855) | (3.531) |
| F-Test | | | (1)=(3) | (2)=(4) |
| | | | [0.999] | [0.999] |
| NT | 33,937 | 33,937 | 33,937 | 33,937 |
| | | Heavy Drinking | | |
| Unemployment Rate | 0.020 | 0.031 | | |
| (County) | (0.037) | (0.043) | | |
| Unemployment Rate | | | 0.091 | -0.394 |
| (State) | | | (0.340) | (0.414) |
| F-Test | | | (1)=(3) | (2)=(4) |
| | | | [0.999] | [0.996] |
| NT | 40,404 | 40,404 | 40,404 | 40,404 |
| | | Obesity | | |
| Unemployment Rate | 0.004 | 0.007 | | |
| (County) | (0.037) | (0.039) | | |
| Unemployment Rate | | | 0.115 | -0.272 |
| (State) | | | (0.306) | (0.339) |
| F-Test | | | (1)=(3) | (2)=(4) |
| | | | [1.000] | [1.000] |
| NT | 37,647 | 37,647 | 37,647 | 37,647 |
| County FE | X | X | X | X |
| State-specific Trends | | X | | X |

* sig. at 10% level  ** sig. at 5% level  *** sig. at 1% level
Notes: Per Table 2a.