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ABSTRACT

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

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. Mental health was also adversely impacted and reports of chronic drinking increased. These effects were concentrated among those with strong labor force attachments. Whites, the less educated, and women were the most impacted demographic groups.

JEL Classification: I0, I12, I14

Keywords: Great Recession, health behaviors, health outcomes, inequality

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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. 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 States by Halliday (2014) who used the Panel Study of Income Dynamics (PSID). Browning and

[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).

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). This paper 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. 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 5 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 National Health Interview Survey (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?

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. To illustrate, we present Figure 1 which shows the unemployment rate during this period. This figure clearly indicates that the recession of 2007-2009 was the most severe. In addition, as shown in Figure 2, unemployment duration during the most recent recession was also, by far, the longest of any recession since World War II peaking at just over 40 weeks.

One recent study that considers the health impact of the Great Recession is Tekin, et al. (2013).[2] They use the Behavioral Risk Factor Surveillance System (BRFSS) and find little impact of the Great Recession on health outcomes using state-level unemployment rates. Our study offers two innovations upon their 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 10 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.* (2016) 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 to this, Bassols, *et al.* (2016) showed that the Great Recession increased legal and illegal drug use in Spain. Finally, Asgeirsdottir, *et al.* (2012) showed that the 2008 economic crisis in Iceland reduced consumption of health compromising goods.

[2] In a similar study, Pabilonia (2015) uses at the Youth Risk Behavior Survey and the American Time Use Survey with a similar research design to investigate the impact of the Great Recession on teenagers' risky behaviors.

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 status, 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 drinking, although these effects were weaker than the impact on self-rated health. Third, we detect the strongest impacts on 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. This is clearly borne out in the empirical evidence as discussed above. 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 two 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 a coping mechanism during stressful times (*e.g.* Dee (2001), Davalos, *et al.* (2012)). 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.

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.[3] We utilize the 2003, 2005, 2007, 2009, 2011 and 2013 waves. The 2003 and 2005 waves correspond to the pre-recession period; 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

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

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 25-55 sample are reported in Table A1. Specifically, we restrict the 25-55 aged 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. 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 1. 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 chronic drinking which we define to be drinking several times per week or every day. 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.

Economic Indicators

We employ data on regional unemployment rates and employment/population (E/P) ratios. These were obtained from the LAUS of the Bureau of Labor Statistics (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, 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. 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.

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. Finally, 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.

County Population Sizes

In Table A2, we report some descriptive statistics on county population sizes from the merged PSID-LAUS-SEER data set. The average county size in the merged data in 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 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.

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 δ_c and δ_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.

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. 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. Note that this would tend to attenuate estimates based on county-level unemployment rates and, so estimates based on them should be viewed as lower bounds in the presence of classical measurement error. 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 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, 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.

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 for the unemployment rate and 125 percent 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 unemployment rates.

Controlling for Heterogeneity

Our study also does a comprehensive job of controlling for heterogeneity across local labor markets. Importantly, Tekin, *et al.* (2013) and Ruhm (2005) only control for state fixed effects which only accounts for the state-level and time-invariant 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. For example, Asians are about one third of the population in San Francisco whereas they are only 0.4 percent of the population of Sierra County in California. In addition, within states, particularly in the South, some counties are “dry” meaning that alcohol cannot be purchased within them. Simple inclusion of state fixed effects would not account for these within state confounders.

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, as shown in Halliday (2014), 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 1 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 the state-specific trend 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 7.8-8.8 percent increases.

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 1 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.

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 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.[4] 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

[4] These results are available upon request.

in small counties. Specifically, we estimate the models for people living in counties with populations above the 15th 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 chronic 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 10 percent level. Note that in columns three and four where we use state-level unemployment rates, both estimates are small in magnitude and not significant, but due to their large standard errors, we cannot reject that these estimates are equal to the estimates at the county level. Moving on to drinking in columns five and six, we see that a one PP increase in the county-level unemployment rate increases the propensity to drink by 0.6-0.8 PP. From Table 1, the mean of this variable is 0.25, so this constitutes a 2.4-3.2 percent increase. The corresponding estimates with the state unemployment rate in columns seven and eight are similar in magnitude, although only the estimate with the state-trends 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 this evidence, the recession had larger effects on whites. Next, looking at drinking, we see tightly estimated and significant effects on drinking behavior for whites. For blacks, the estimates are less tightly estimated and only the estimate with the state-trends is significant in column six. However, the magnitudes are larger for blacks than for whites. 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 1.3 PP but *decreases* the propensity for whites by 0.5 PP. However, these results are not robust to the inclusion of state-trends in the final column. Our interpretation of these results is that there is stronger evidence that the recession impacted the health of white Americans than black Americans.

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 and drinking when state-trends are included in column six. 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 1 percent level. The corresponding estimates for men are 0.004 and 0.005 and neither is tightly estimated. Similarly, we see that a 1 PP increase in the unemployment rate increase the probability of chronic drinking for women by 0.8 PP and both estimates are significant at the 10 percent level. The corresponding estimates for men are 0.005 and 0.008 but neither is 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 reports of chronic drinking. The bulk of our effects were borne by whites, the less educated, and women. We do not uncover any evidence that macroeconomic measures at larger levels of aggregation have larger effects than at smaller levels and, thus, this paper provides no evidence of spillovers.

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. However, they are consistent with a growing body of evidence that employs individual-level data and shows that health tends to deteriorate when the economy worsens. Moreover, we show that the people who were the most impacted were less educated, white, female, and younger than age 55. 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.

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Figure 1: Total Unemployment Rate in Each Recession since Postwar

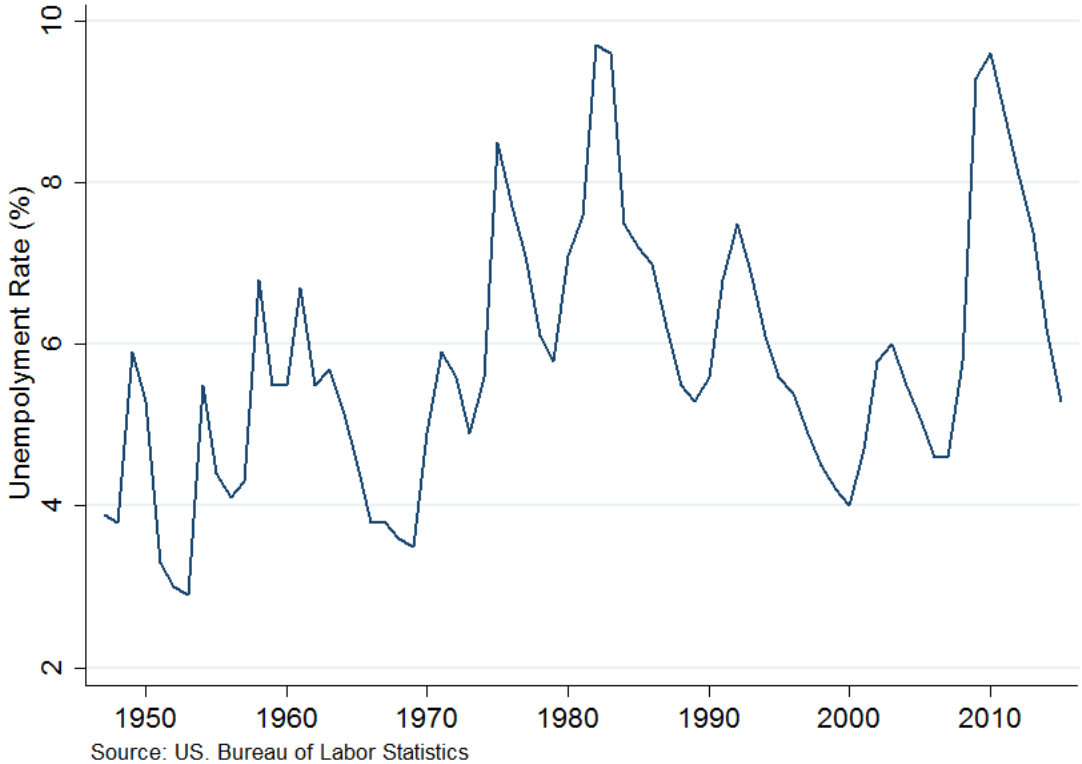

Figure 2: Unemployment Duration since Postwar

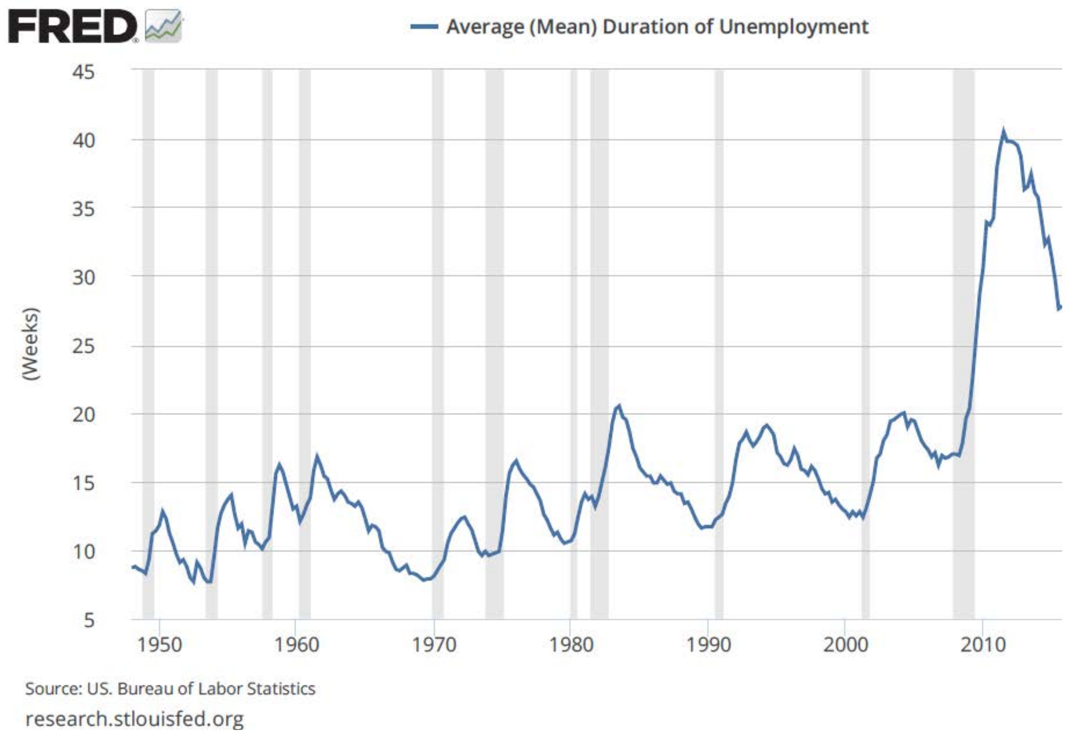

Figure A1: Kernel Density of County Populations

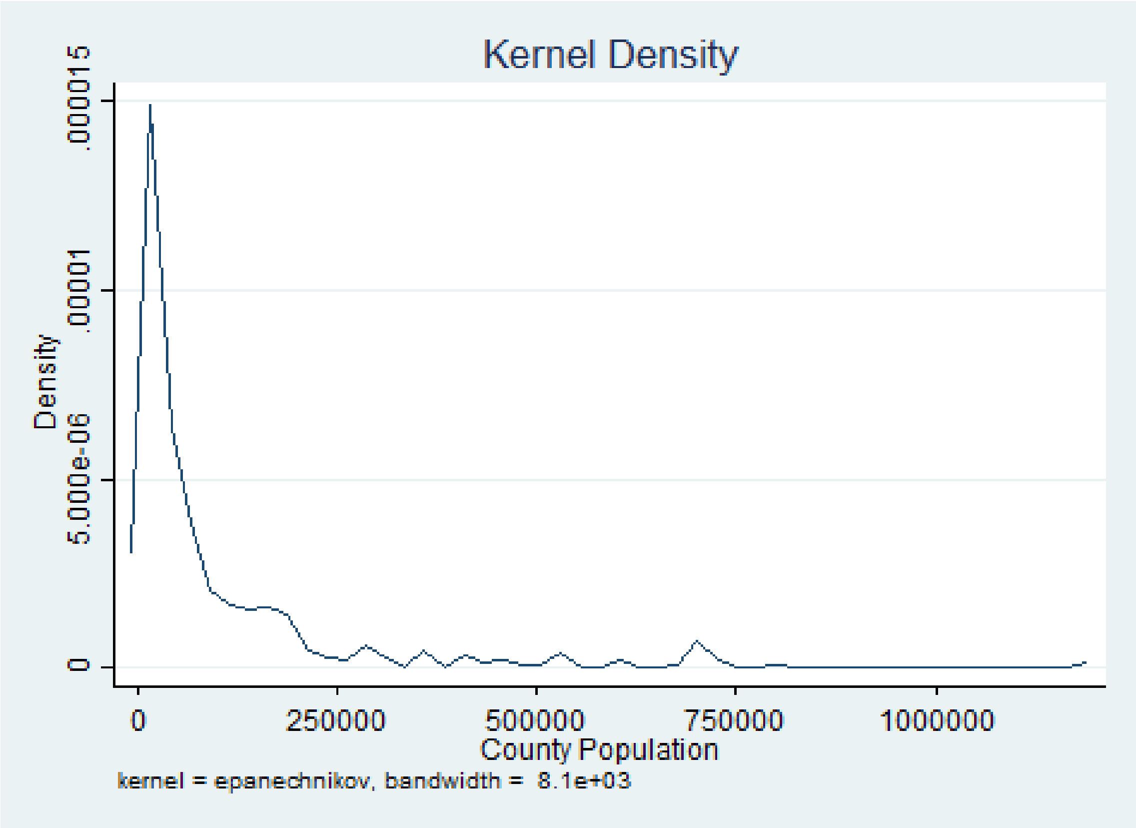

Table 1: Descriptive Statistics

	Age 25 - 55			Age 65 +		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Economic Conditions						
County Employment to Population Ratio	43280	0.56	0.09	9185	0.56	0.09
State Employment to Population Ratio	43280	0.60	0.04	9185	0.59	0.04
County Unemployment Rate(%)	43240	6.95	2.75	9177	7.04	2.64
State Unemployment Rate (%)	43280	6.88	2.20	9185	6.99	2.18
Health Outcomes						
Chronic Drinking	24311	0.25	0.43	3360	0.31	0.46
K6 Index	35739	2.98	3.50	7138	2.60	3.57
Poor Health	42964	0.09	0.28	9060	0.32	0.47
Obesity	41903	0.26	0.44	8847	0.22	0.42
Demographic Controls						
Age	43280	40.88	8.84	9176	75.25	7.60
Sex	43280	0.52	0.50	9185	0.43	0.50
Married	43275	0.67	0.47	9185	0.54	0.50
Never married	43275	0.16	0.37	9185	0.02	0.15
Widowed	43275	0.01	0.10	9185	0.33	0.47
Divorced	43275	0.13	0.34	9185	0.10	0.30
Less than High School	41205	0.07	0.26	8635	0.18	0.38
High School Graduated	41205	0.32	0.47	8635	0.40	0.49
College	43280	0.63	0.48	9185	0.45	0.50
White	42608	0.80	0.40	9030	0.87	0.33
Black	42608	0.13	0.33	9030	0.08	0.27

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
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)							0.010*** (0.002)	0.009*** (0.003)				
Emp/Pop Ratio (County)									0.028 (0.030)	0.004 (0.030)		
Emp/Pop Ratio (State)											-0.575** (0.212)	-0.433 (0.289)
F-Test							(1)=(7) [0.984]	(2)=(8) [0.995]			(9)=(11) [0.976]	(10)=(12) [0.995]
County FE	X	X			X	X	X	X	X	X	X	X
Individual FE			X	X								
State-specific Linear Trends		X		X		X		X		X		X
Non-mover Sample					X	X						
NT	40,721	40,721	40,721	40,721	25,142	25,142	40,761	40,761	40,761	40,761	40,761	40,761

* 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. We report the p-value for the F-tests in brackets.

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Unemployment Rate (County)	0.008*** (0.002)	0.007*** (0.002)	0.008*** (0.003)	0.008*** (0.003)	0.009*** (0.003)	0.007*** (0.003)						
Unemployment Rate (State)							0.010*** (0.003)	0.008*** (0.003)				
Emp/Pop Ratio (County)									0.034 (0.041)	-0.005 (0.045)		
Emp/Pop Ratio (State)											-0.596** (0.254)	-0.659* (0.393)
F-Test							(1)=(7) [0.984]	(2)=(8) [0.995]			(9)=(11) [0.976]	(10)=(12) [0.995]
County FE	X	X			X	X	X	X	X	X	X	X
Individual FE			X	X								
State-specific Linear Trends		X		X		X		X		X		X
Non-mover Sample					X	X						
NT	34,651	34,651	34,651	34,651	17,394	17,394	34,691	34,691	34,691	34,691	34,691	34,691

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

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	K6 Depression Index				Chronic Drinking				Obesity			
Unemployment Rate (County)	0.053*	0.057*			0.006*	0.008**			-0.002	-0.001		
	(0.028)	(0.030)			(0.003)	(0.003)			(0.003)	(0.003)		
Unemployment Rate (State)			0.042	0.046			0.005	0.009*			-0.001	0.001
			(0.031)	(0.039)			(0.004)	(0.005)			(0.003)	(0.003)
F-Test			(1)=(3)	(2)=(4)			(5)=(7)	(6)=(8)			(9)=(11)	(10)=(12)
			[0.999]	[0.999]			[0.999]	[0.998]			[0.999]	[0.999]
County FE	X	X	X	X	X	X	X	X	X	X	X	X
State-specific Linear Trends		X		X		X		X		X		X
NT	33,937	33,937	33,937	33,937	23,288	23,288	23,307	23,307	39,774	39,774	39,813	39,813

* 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		Chronic Drinking		Obesity	
Unemployment Rate (County)	-0.003 (0.005)	-0.002 (0.005)	0.012 (0.049)	0.022 (0.052)	-0.001 (0.011)	-0.006 (0.012)	-0.003 (0.004)	-0.004 (0.004)
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	3,212	3,212	8,377	8,377

* 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)	(5)	(6)	(7)	(8)
				Blacks				
	Poor Health		K6 Depression Index		Chronic Drinking		Obesity	
Unemployment Rate (County)	0.003	-0.001	-0.047	-0.025	0.012	0.022**	0.013*	0.011
	(0.006)	(0.006)	(0.073)	(0.087)	(0.010)	(0.011)	(0.007)	(0.007)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
N	12,929	12,929	10,795	10,795	6,404	6,404	12,673	12,673
				Whites				
County Unemployment Rate	0.008***	0.007***	0.061**	0.069**	0.007**	0.009**	-0.005*	-0.003
	(0.002)	(0.002)	(0.030)	(0.033)	(0.004)	(0.004)	(0.003)	(0.003)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
NT	25,538	25,538	21,238	21,238	15,870	15,870	24,936	24,936

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

Table 6: Effects by Education, Ages 25-55

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High School Education (at most 12 years of schooling)							
	Poor Health		K6 Depression Index		Chronic Drinking		Obesity	
Unemployment Rate (County)	0.008**	0.007*	0.048	0.034	0.006	0.013*	-0.006	-0.006
	(0.004)	(0.004)	(0.041)	(0.045)	(0.006)	(0.007)	(0.005)	(0.005)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
N	15,977	15,977	13,073	13,073	8,207	8,207	15,649	15,649
	College Graduates							
County Unemployment Rate	0.004	0.002	0.019	0.041	0.008	0.004	-0.002	0.001
	(0.003)	(0.003)	(0.042)	(0.048)	(0.006)	(0.006)	(0.004)	(0.004)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
NT	12,205	12,205	10,430	10,430	8,115	8,115	11,932	11,932

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

Table 7: Effects by Gender, Ages 25-55

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Men							
	Poor Health		K6 Depression Index		Chronic Drinking		Obesity	
Unemployment Rate (County)	0.004	0.005*	0.058*	0.050	0.005	0.008	0.001	0.003
	(0.002)	(0.003)	(0.032)	(0.035)	(0.005)	(0.005)	(0.003)	(0.004)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
N	20,560	20,560	17,093	17,093	12,673	12,673	20,338	20,338
	Women							
County Unemployment Rate	0.010***	0.007**	0.043	0.052	0.008*	0.008*	-0.008*	-0.007*
	(0.003)	(0.003)	(0.040)	(0.044)	(0.004)	(0.004)	(0.004)	(0.004)
County Fixed Effects	X	X	X	X	X	X	X	X
State-specific Trends		X		X		X		X
NT	20,161	20,161	16,844	16,844	10,615	10,615	19,436	19,436

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

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 from the Merged Data

Mean	99555
Standard Deviation	160419
10^{th} Percentile	7003
25^{th} Percentile	14976
50^{th} Percentile	35341
75^{th} Percentile	117498
90^{th} Percentile	227014