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Local labor market fluctuations and health: Is there a connection and for whom?

Kerwin Kofi Charles [a], Philip DeCicca [b,*]

[a] University of Chicago and NBER, United States
[b] McMaster University, Department of Economics, 1280 Main Street West, Kenneth Taylor Hall, Rm. 422, Hamilton, Ontario, Canada L8S 4M4

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ABSTRACT

We examine the relationship between local labor market conditions and several measures of health and health behaviors for a sample of working-aged men living in the 58 largest metropolitan areas in the United States. We find evidence of procyclical relationships for weight-related health and mental health for men with low ex ante employment probabilities. Separate estimates suggest worsening labor market conditions lead to weight gains and reduced mental health among African-American men and lower mental health among less-educated males. Among our findings, those related to mental health are most pronounced.

1. Introduction and background

Economists have devoted much attention to the impact of macroeconomic fluctuations on a variety of outcomes, including earnings and their distribution, employment, criminal activity and human capital investment. While interest is rising, they have paid less attention to a possible connection to health. Using repeated cross-sectional data from the National Health Interview Surveys (NHISs), we estimate relationships between local labor market conditions and several measures of health and health behaviors for a sample of individuals living in the 58 largest metropolitan statistical areas (MSAs) in the United States. The paper's primary contributions are threefold: (1) we consider local rather than more aggregate labor market fluctuations, (2) we explore more detailed measures of mental health, and (3) we examine whether economic conditions have larger impacts on individuals with relatively poorer labor market prospects.

The paper proceeds as follows: in the remainder of this section, we discuss why health may vary with local labor market fluctuations, whose health might be most affected and briefly review the relevant literature. In Section 2, we describe our data, focusing on key variables and the construction of our analysis sample, which consists of working-aged men. Section 3 presents our empirical strategy which relates local labor market conditions, via MSA-level unemployment rates, to measures of health and health behaviors that may vary over short periods of time. Since the effect of labor market conditions on health may depend on the extent to which one's present or prospective employment is impacted by them, we divide our sample into

* Corresponding author.
E-mail addresses: kcharles@uchicago.edu (K.K. Charles), decicca@mcmaster.ca (P. DeCicca).

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groups whose employment prospects are potentially more and less likely to be affected by such fluctuations. For example, we allow the effect of local labor market conditions to vary by race and education group since previous research suggests the labor market outcomes of non-white and less educated individuals are relatively more impacted by economic fluctuations. In addition, we allow this effect to vary by one's potential "exposure" to labor market fluctuations, as proxied by their predicted employment status. Section 4 presents our principal findings and briefly discusses them. For those men least likely to be employed, we find evidence of a procyclical relationship for weight-related health and mental health. Consistent with these findings, we present evidence that worsening labor market conditions lead to weight gains and reduced mental health among African-American men and lower mental health among less educated males. Among these findings, those related to mental health are most pronounced. This is significant given the connection of mental health to other phenomena such as homelessness, drug abuse and criminal activity. It is also important since it may provide information to policymakers on how best to allocate scarce health resources. Section 5 discusses our most prominent findings and Section 6 concludes the paper.

1.1. Why might local labor market conditions affect health?

Conceptually, local labor market conditions may affect health for a variety of, potentially conflicting, reasons. Two general explanations have gained prominence in related work. The first can be classified as a "behavioral" explanation since it implies that health impacts propagate through changes in individual behavior, while the second can be considered a "structural" explanation as it implies labor market conditions can affect health absent any explicit behavioral changes by individuals. To elaborate, we briefly consider each in the context of a labor market contraction.

First, local labor market fluctuations might impact health through changes in the opportunity cost of time. When the unemployment rate rises, employment is reduced on intensive and extensive margins. Such reductions lower the opportunity cost of other, non-market activities including household production. One form of household production that is very time-intensive is the production of health.[1] Facing lower time costs, affected individuals may spend more time in activities intended to improve their health (e.g., exercising, producing and consuming homemade rather than mass-produced or restaurant meals, or using preventive medical services). If investment in such activities improves health and does so in a reasonably short period of time, a countercyclical relationship between labor market conditions and health will obtain.[2]

Another channel through which fluctuating labor market conditions might affect health is sometimes referred to as the "economic stress" hypothesis (c.f., Catalano and Dooley, 1983; Catalano, 1991). In general, the idea is that a weaker economy leads to increased stress due to greater uncertainty of present and future income receipt. In turn, this greater stress level leads to reductions in health.[3] In addition, such uncertainty over income may have "feedback" effects in that it may increase the likelihood of life events such as bankruptcy or marital dissolution which may add to the stress associated with a downturn in the labor market. If the stress hypothesis is operative and if greater stress reduces health in the short-run, a procyclical relationship between labor market conditions and health will obtain.[4]

1.2. Who might be most affected by labor market fluctuations?

While these two general explanations are not mutually exclusive and certainly do not exhaust the mechanisms through which labor market conditions may affect health, they do indicate that their directional impact on health is an empirical question. A separate issue is whose health is most likely to be impacted by such fluctuations.

Since the question of interest is whether *labor market* conditions impact health, individuals whose current employment or employment prospects are most affected by labor market fluctuations may be most likely to experience corresponding changes in health, if such effects exist. But who are these individuals? Previous work suggests the labor market outcomes of "lower-skilled" individuals are disproportionately affected by economic fluctuations. Of these studies, the ones that use MSA-level variation in labor market conditions to examine labor market outcomes such as earnings and employment are most relevant to this study (Bartik, 1991, 1993a,b, 1994, 1996; Bound and Holzer, 1993, 1995). Generally speaking, these authors find greater sensitivity to economic fluctuations among non-whites, younger individuals and individuals with lower education levels. That is, these groups are relatively more likely to have positive labor market outcomes during economic expansions and negative ones when labor market conditions deteriorate.[5] While not as directly relevant, studies which use national-level variation or focus on younger individuals tend to find similar patterns (c.f., Blank, 1989; Acs and Wissoker,

[1] As anyone who has ever purchased a piece of exercise equipment knows, investment in health can also be quite goods-intensive, but inherently involves a substantial time component.

[2] Of course, reductions in the opportunity cost of market time make time spent in other, potentially health-reducing activities less costly as well (e.g., late nights spent at a local tavern).

[3] Realized income losses may have more direct impacts on health. For example, when income decreases it is likely that the ability to finance "healthy" goods such as fruits and vegetables falls for some individuals. Conversely, a loss in income may reduce high calorie or calorie-dense restaurant meals to the extent that these are normal goods.

[4] A distinction should be made between this type of stress and *job-related* stress since it is quite plausible that economic contractions reduce the latter. For example, it is likely that mandatory overtime and, more generally, worker effort fall during labor market contractions.

[5] Note that most of these studies offer no direct evidence on *why* "lower skilled" individuals are relatively more impacted, but tend to speculate that the observed relationship is due to lack of geographic mobility and/or because their employment is concentrated in sectors that are most impacted by economic changes.

1991; Freeman, 1991). More recently, a comprehensive study by Hoynes (2000) finds that the labor market outcomes of non-whites and those with lower levels of education are relatively more impacted by changes in local labor market conditions.[6] In particular, she finds that these groups are more likely to experience reductions in employment and earnings in a contraction, and more likely to experience gains in these areas in subsequent recoveries, relative to their white and more educated counterparts. Based on this evidence, we allow the impact of local labor market conditions on various measures of health and health behaviors to vary across race and education groups, as discussed in Section 3.

Note, however, that individuals whose employment status or prospects are not directly impacted by labor market fluctuations might also experience health effects. Consider the following examples in the context of a labor market expansion. First, for individuals who remain without jobs in an expansion, government programs that provide cash or other in-kind benefits may be less likely to expire or otherwise be curtailed (e.g., unemployment insurance, job training, etc.). On the other end of the spectrum, those with relatively secure employment may be impacted since such individuals may experience improved job mobility or job characteristics (e.g., higher real wages or more generous fringe benefits) in an expansion. Such individuals may also be impacted because of more intense work schedules (e.g., more hours worked per week) associated with an economic expansion. So, while it seems reasonable to expect that labor market conditions might affect the health of individuals whose labor market fortunes are most directly impacted by them, it is also possible that they affect health across a wider range of individuals and that they do so in a heterogeneous fashion.

Finally, note that such potential indirect effects of labor market conditions on health (i.e., impacts on health that do not work through explicit changes in employment status) affect our choice of empirical strategy. As described in Section 3, we estimate a reduced form model of the impact of local unemployment rates on various measures of health and health behaviors, rather than a more structural model (e.g., instrumenting endogenous employment status with local unemployment rates) which would miss the kind of indirect impacts on health discussed above. In taking a reduced form strategy, we are consistent with the relevant literature which we describe below.

1.3. Related work

While the present work is related conceptually to the literature that investigates the impact of employment *status* on health, we limit description to those studies that examine the connection between labor market conditions and health. In particular, we describe three recent studies most closely related to ours.

In the first rigorous study of its kind, Ruhm (2000) examines the impact of state-level unemployment rates on state-specific measures of total mortality and 10 specific causes of death which account for roughly three-fourths of all deaths in the United States.[7] He finds evidence of a countercyclical relationship for total mortality and 8 of the 10 specific causes examined.[8] While automobile-related fatalities account for a substantial portion of the impact of changes in state unemployment rates on total mortality, the author finds that preventable causes of death account for an even greater portion of total deaths. Moreover, he also examines age-specific death rates and finds that fatalities among those aged 20–44 are most sensitive to changes in state labor market conditions, consistent with the idea that his estimates are capturing a labor market phenomenon. Finally, he finds that the suicide rate varies directly with the state unemployment rate, suggesting that *mental* health is procyclical in nature.

Second, Ruhm (2001), using data on individuals residing in 31 "large" MSAs from the 1972 to 1981 NHISs finds evidence of a countercyclical relationship between state unemployment rates and several indicators of physical health including medical care utilization (e.g., hospital episodes and doctor visits), unhealthy days (e.g., restricted-activity days and bed days) and whether an individual experienced an acute, but not chronic, medical condition. The author allows the impact of state unemployment rates to vary across certain groups and finds these relationships are most pronounced for males, employed persons and working-aged individuals.[9] Finally, consistent with his earlier finding regarding suicide, he finds that non-psychotic mental disorders rise with increases in state unemployment rates and concludes that this represents "some evidence that mental health is procyclical."

Of the studies described, Ruhm (2005) is most relevant to the present work because of the generally greater overlap in outcomes examined.[10] Using data on individuals aged 18 and older from the 1987 to 2000 waves of the Behavioral Risk Factor Surveillance Survey (BRFSS), the author finds countercyclical relationships between state unemployment rates and several health behaviors. In particular, he finds systematic relationships for smoking, physical inactivity and weight-related health. Consistent with Ruhm (2001), he finds that these relationships are, generally speaking, most pronounced for males and employed persons. Finally, the author presents evidence that suggests the impacts are considerably larger in the first half of the period in question. In particular, estimates from models that include only observations for the years 1987–1994 are considerably larger in magnitude than estimates that include all years. This is especially true in models that examine smoking behavior and obesity.

[6] Hoynes (2000) defines labor markets as MSAs and uses 35 MSAs in her analysis.

[7] The author also explores behavioral reasons that might explain these findings, but the majority of this work is included in a separate study which we discuss in detail later in this section.

[8] The two exceptions are cancer and suicide.

[9] Consistent with these findings, he reports systematic evidence that among chronic conditions "back disorders" are countercyclical.

[10] The exception is that Ruhm (2005) does not examine outcomes related to mental health.

In general, the preceding work suggests opposite effects of economic conditions on physical and mental health. In particular, while there is relatively less evidence related to mental health, what is available suggests that mental health is procyclical while physical health, and the health behaviors that may influence it, are countercyclical.

2. Data

We use annual cross-sectional data from the NHIS for the years 1997–2001, inclusive. While the NHIS dates back to 1972, it was redesigned in the middle 1990s, with 1997 the first wave following this revision. We use the adult sample which consists of annual surveys of 30,000–35,000 individuals. To obtain a more localized measure of labor market conditions, we limit our analysis to individuals living in Level A or "large" MSAs, for whom MSA of residence is publicly available.[11] This restriction yields between 50 and 55% of the overall NHIS sample, depending on the year in question. In 1997, such metropolitan areas contained roughly 52% of the U.S. population. In the following paragraphs, we describe our key variables, focusing on measures of health that may fluctuate with changing labor market conditions and the MSA-level unemployment rate, which we use as a proxy for these conditions. Finally, we provide detailed information on our analysis sample.

2.1. Health measures

Conditional on availability, we focus on measures of health that may vary over short periods of time and whose existence is apparent independent of access to medical care. These measures can be grouped into two general categories: weight-related health and psychological well-being, a proxy for mental health. We also examine a large set of health behaviors which includes cigarette smoking, heavy alcohol consumption and frequency of physical exercise.

2.1.1. Weight-related health

In terms of weight-related health, we focus on body mass index (BMI) and clinically relevant thresholds based upon it. BMI is defined as the ratio of one's weight in kilograms to their height in meters squared. While BMI is preferred to body weight, and is a generally accepted metric to assess weight-related health, it has certain shortcomings. First, BMI might not be a valid measure for some individuals, perhaps due to differences in body type or composition. If not, widely used thresholds at the upper and lower tails of the distribution may misrepresent weight-related health. Second, BMI information in the NHIS is constructed from self-reports of height and weight, so it is subject to measurement error (Cawley, 1999).[12] In particular, it is likely that heavier individuals tend to under-report weight while lighter individuals over-report it. As noted by Lakdawalla and Philipson (2002), such systematic reporting may attenuate estimated coefficients rather than merely reduce their precision, as with classical measurement error in the dependent variable.

In addition to BMI, itself, we examine three thresholds of clinical interest, including underweight (BMI $\leq$ 18.5), overweight (BMI $\geq$ 25) and obesity (BMI $\geq$ 30). In addition, we model the BMI $\geq$ 35 and 40 thresholds to examine effects in the extreme upper portion of the BMI distribution.[13] We also combine the first three of these thresholds to examine what happens to the fraction of individuals whose body weight falls into one of four "healthy" ranges—BMI between 18.5 and 25, BMI between 18.5 and 30, BMI between 20 and 25 and BMI between 20 and 30. To the extent that local labor market conditions lead to weight gain in some individuals and weight loss in others, these are useful measures of weight-related health.

2.1.2. Mental health

With respect to mental health, the NHIS includes six questions that assess an individual's state of mind in the month prior to being interviewed. These questions comprise the *K6 Non-specific Psychological Distress* scale which was designed to identify individuals who are likely to have both a diagnosable mental disorder and significant impairment. Validation studies demonstrate that this particular scale is at least as effective as more comprehensive and more established scales in diagnosing "serious mental illness". In particular, Kessler et al. (2003) provide evidence that the K6 scale is at least as effective in such diagnosis as the longer "K10" scale, the Composite International Diagnostic Interview Short-Form (CIDI-SF) and the World Health Organization Disability Assessment Schedule (WHO-DAS) which have been used extensively.

The six questions that comprise the K6 scale are as follows: during the past 30 days, how often did you feel. . ..

. . .so sad that nothing could cheer you up?
. . .hopeless?
. . .worthless?

[11] Level A MSAs have at least 1 million residents. Due to a lack of MSA identifiers we cannot use data beyond 2001. However, as detailed later, the years examined are particularly relevant since they contain both a period of economic expansion and a period of contraction.

[12] While height and weight are self-reported, they were gathered via in-person interviews rather than, say, over the phone. It is likely that such interviews constrain individuals' ability to misreport their height and weight.

[13] The latter threshold is referred to as "morbid" obesity in the clinical literature.

. . .restless or fidgety?
. . .nervous?
. . .that everything was an effort?

Legitimate responses include "all of the time", "most of the time", "some of the time", "a little of the time" and "never".[14] To assess how within-MSA changes in local unemployment rates affect reporting patterns, we parameterize responses to each of these six questions into three separate dichotomous indicators. In particular, we estimate three sets of models where the dependent variables equal 1 if the respondent answers "most of the time, or more frequently", "some of the time, or more frequently", and "never". To be clear, the dependent variable in the "some of the time, or more frequently" models equals 1 if the respondent answers "some of the time", "most of the time" or "all of the time" and 0 otherwise. Similarly, the "most of the time, or more frequently" models' dependent variable equals one if the respondent answers "most of the time" or "all of the time" and zero otherwise. The "never" models provide a check on estimates from the other two sets of models in that the coefficient on local unemployment rate should have the opposite sign, though, strictly speaking, this is not required. Finally, we do not model the "all of the time" response due to relatively small cell sizes.

2.1.3. Health behaviors

Health behaviors analyzed include cigarette smoking, alcohol consumption and various measures of physical exercise. We label someone a smoker if he reports smoking cigarettes on at least some days per week. Since the cigarette excise tax rate has been shown to be an important determinant of smoking behavior, we also include state-level cigarette taxes in these models.[15] Detailed information on alcohol consumption is somewhat less available in the NHIS and we focus on measures that represent "heavy" drinking. In particular, we model the number of days in the 12 months prior to being interviewed that an individual consumed five or more alcoholic drinks. We also model two thresholds based on this measure—whether the individual has participated in any days of heavy drinking in the past year and whether he has engaged in 50 or more such days over the same time frame. The latter measure is intended to capture heavy drinking that occurs on a fairly regular basis—in this case, weekly. Finally, information on exercise includes "moderate" and "vigorous" exercise as well as information on strength training. Moderate exercise is defined as exercise that causes "only light sweating or slight to moderate increases in breathing or heart rate" while vigorous exercise is defined as exercise that causes "heavy sweating or large increases in breathing or heart rate". Data on "moderate" and "vigorous" exercise include information on the number of times per week an individual engages in either type of activity for at least 20 min.[16] Data on strength training include no time component and refer only to the number of times per week an individual engages in such activity, irrespective of the time spent at each session. For completeness, we define three dependent variables that measure the frequency of each of these three types of exercise: Any times per week, three or more times per week, and five or more times per week.

2.2. Local labor market conditions

We use MSA-level unemployment rates from the Bureau of Labor Statistics' Local Area Unemployment Statistics database as a proxy for local labor market conditions.[17] As indicated earlier, previous work relating the unemployment rate to health has focused on state-level measures, implicitly treating the state as the labor market of relevance. Since the usefulness of more localized measures depends on the existence of independent variation relative to more aggregate measures, we regress MSA-level unemployment rates on corresponding state unemployment rates with aggregate data. Since 3 of the 58 MSAs, involve substantial overlap with multiple states we drop these from our regression models. This restriction results in a sample size of 1100, which is the number of eligible MSAs (55) multiplied by the number of quarters (20). The resulting regression yields an R^2 of less than 0.33, even when quarter and year indicators are added to the model. Hence, there seems to be substantial variation in local unemployment rates, relative to corresponding state measures.

Though we use only 5 years (20 quarters) of data, they cover a period of economic expansion and contraction. Fig. 1 presents national, seasonally adjusted unemployment rates by quarter. From this figure it is apparent that the U.S. economy was expanding in the first 14 quarters of our data, before the initiation of economic contraction. In other words, our period, though somewhat short, contains both a period of economic expansion and one of economic contraction. Since MSA-level unemployment rates are not seasonally adjusted, we present sample-specific figures based on annual, rather than quarterly, unemployment rates. As seen in Fig. 2, the unemployment rate falls and then rises, for a nearly U-shaped relationship over the period in question. Examining this pattern by groups defined by predicted employment status (Fig. 3),

[14] Clinicians typically assign equal point values to response levels and an individual is labeled "seriously mentally ill" when a certain threshold is exceeded. However, since this masks potentially important variation in response to the individual questions that comprise the scale, we model selected responses to each question separately, as described below.

[15] More importantly, there is substantial variation in taxes over this period and this variation may be correlated with economic conditions (e.g., states may raise sin taxes during economic downturns to increase revenues). Note also that we use state population-weighted averages to assign cigarette tax rates to individuals residing in MSAs that overlap one or more states.

[16] For the first 6 months of 1997 questions regarding moderate and vigorous exercise were asked in terms of "at least 10 min per day, rather than "at least 20 min", as asked in all subsequent periods. For consistency, we drop individuals interviewed in the first 6 months of 1997 from these models.

[17] See www.bls.gov/lau.

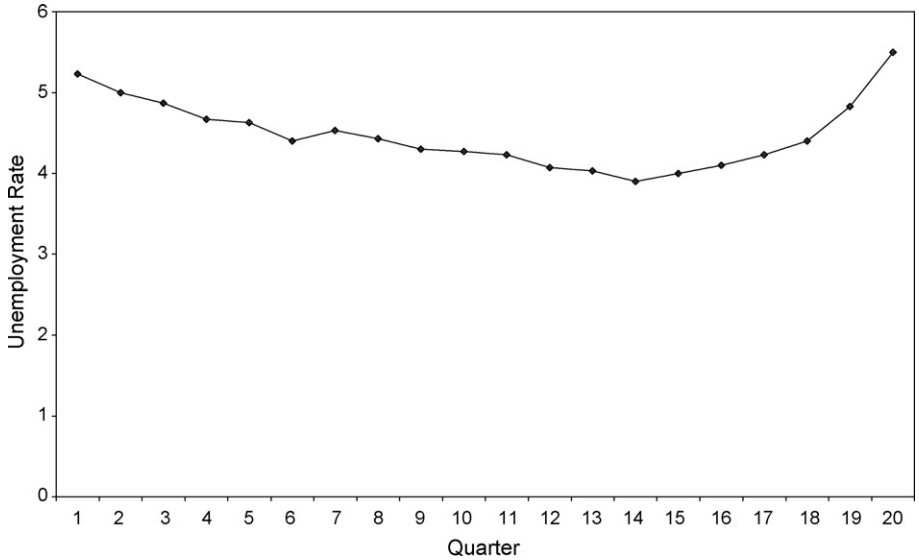

Fig. 1. Quarterly unemployment rate, 1997–2001.

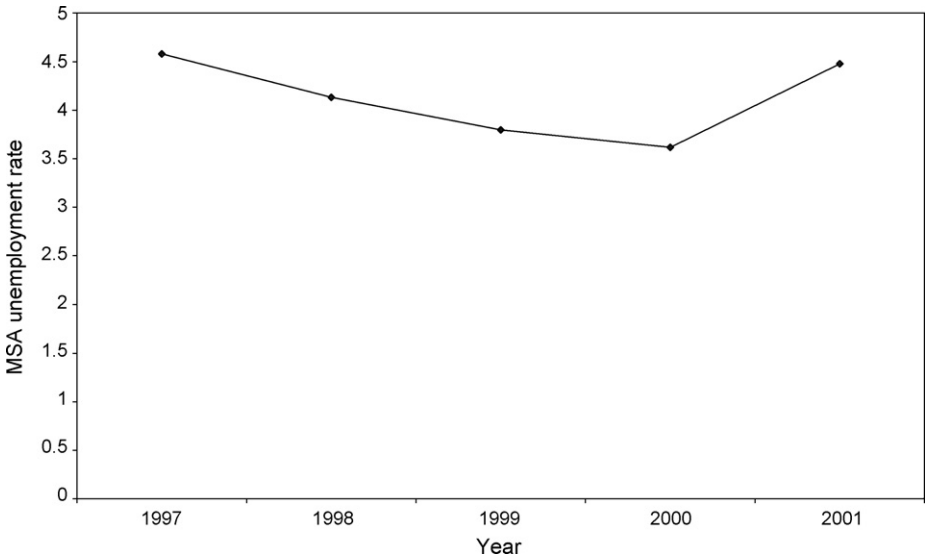

Fig. 2. Unemployment rate, 1997–2001.

race (Fig. 4) and level of education (Fig. 5) shows that the same U-shaped relationship obtains. Not surprisingly, these sample-specific patterns reflect the national pattern exhibited in Fig. 1. Finally, note that the roughly parallel lines within Figs. 3–5 indicate very similar experiences over time, though the gaps indicate level differences in average unemployment regime.

2.3. Analysis sample

Restricting our sample to those men who live in large MSAs, as described above, yields 38,101 men from 5 years of data. We limit our sample to men for traditional reasons (e.g., degree of connection to labor force issues) as well as issues related to late 1990s welfare reform which may make identification of labor market effects, especially among plausibly disadvantaged women, particularly difficult.[18] We further limit our sample to males between 24 and 59 years old. On the upper end of this range, we aim to avoid retirement issues which may be affected by local labor market conditions. On the lower end,

[18] For example, Bitler et al. (2004) find evidence that welfare reform affected the health of single mothers.

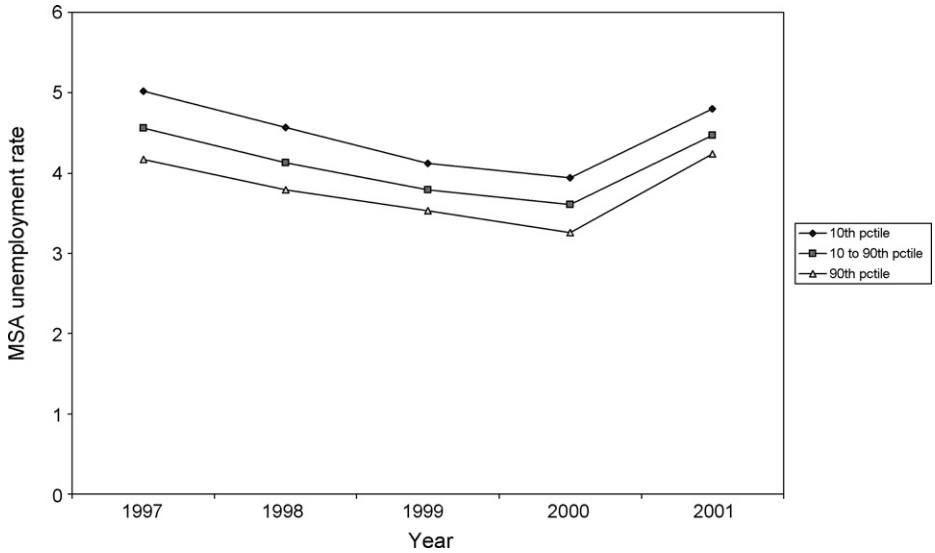

Fig. 3. Unemployment rate by percentiles of the predicted employment distribution.

we want to avoid schooling or training issues, since labor market conditions may also influence these decisions. These age restrictions reduce our sample to 27,159 men. Since we include indicator variables for missing data on other covariates, this figure represents the sample we use to generate most estimates discussed in Section 4, though note that missingness in the dependent variable, itself, reduces sample size in specific models.

3. Empirical strategy

Unobserved heterogeneity is a primary concern in relating local labor market conditions and health. More precisely, the concern is that unobserved labor market characteristics that are correlated with the unemployment rate and exert an independent influence on health will result in biased estimates. For example, some geographic areas may experience both poor health and high unemployment though no causal relationship exists. In a single cross-section of data, this would induce a procyclical relationship where none may exist. The repeated cross-sectional nature of NHIS data allows for inclusion of MSA fixed effects, which will eliminate the troublesome heterogeneity if it is time-invariant over the period in question.

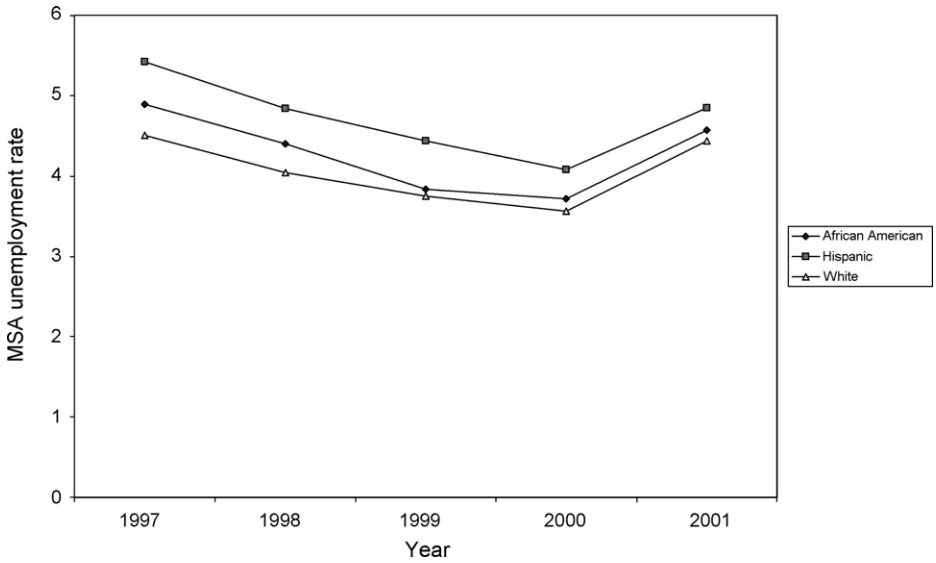

Fig. 4. Unemployment rate by race.

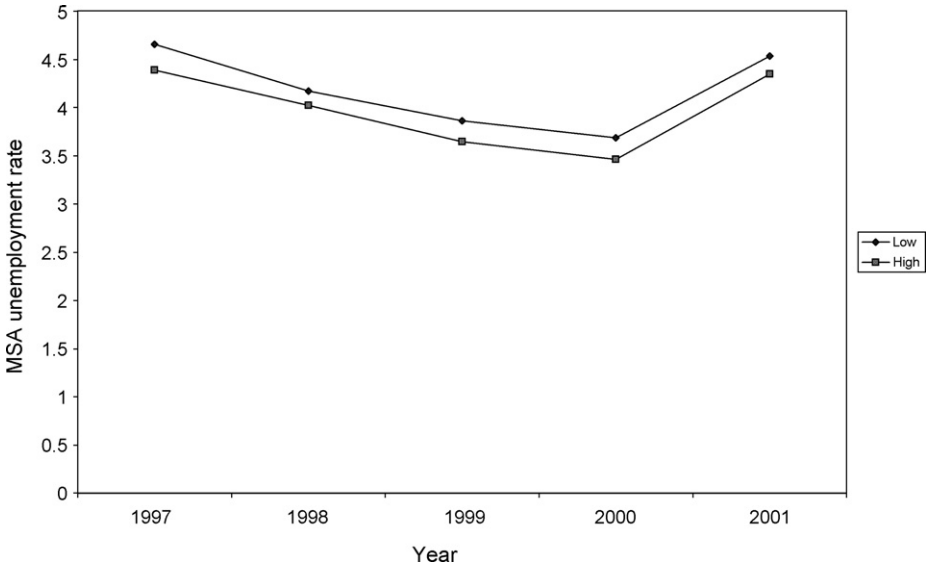

Fig. 5. Unemployment rate by education level.

With this in mind, a model that bases statistical identification on within-MSA variation in the unemployment rate is given by

$$\mathbf{H}_{ijqt} = \tau \mathbf{U}_{jqt} + \beta \mathbf{X}_{ijqt} + \mu_j + \theta_q + \gamma_t + \varepsilon_{ijqt} \tag{1}$$

Here, i indexes the individual, j MSA of residence, q quarter surveyed, and t year surveyed; **H** represents the relevant measure of health or health behavior; **U** the MSA-specific unemployment rate; **X** a set of individual and MSA-specific covariates; μ is a vector of MSA fixed effects; θ is a set of quarter fixed effects; γ represents year effects, and ε captures unobserved determinants of health.[19] With the exception of models that condition on its elements, the vector **X** includes controls for age, race, educational attainment, prior year's household income as a fraction of the poverty line, marital status and employment status.[20] All models include MSA and time fixed effects as specified in Eq. (1) and we report robust standard errors clustered on MSA, rather than MSA-time cells (Bertrand et al., 2004). That said, reported standard errors are substantively invariant to clustering by MSA-Year cells and MSA-Year-Quarter cells.

This specification, however, imposes the same relationship between local labor market conditions and health for all individuals. As discussed earlier, previous work on the distributional impacts of economic conditions on employment-related outcomes suggests that lower skilled individuals, particularly non-white and less educated individuals, are most affected by such fluctuations. To address this shortcoming, we take two distinct approaches. First, we allow the effect of the local unemployment rate to vary by an individual's "exposure" to labor market fluctuations. Since exposure is not directly observable, we proxy it via an individual's predicted employment status. In particular, we first estimate a cross-sectional model of employment status using 1997 data, which is intended to capture the data generating process for employment status prior to subsequent fluctuations in the local unemployment rate. Using estimated coefficients from this model, we compute predicted employment probabilities for all individuals with useable employment and MSA of residence information.[21] We then estimate models that interact this predicted value with the local unemployment rate in order to understand whether the impact of labor market conditions on health varies across this distribution. Table 1 presents estimates for a small number of selected outcomes.[22] As can be seen, coefficients on the interaction term suggest differences in the impact of local unemployment rate. For example, in models with outcomes related to weight-related health (columns 1 and 2) and mental health (columns 3 and 4) coefficients on the relevant interaction terms suggest the procyclical relationships implied by the

[19] Aside from the different geographic definition of a labor market (MSA versus state), this specification is conceptually identical to that used by Ruhm (2005). Note also that we include the quarter fixed effects since MSA-level unemployment rates are only available in seasonally unadjusted form. Finally, we also estimate models with year-specific quarter fixed effects, instead of separate quarter and year effects, and find substantively identical results to those presented in Section 4.

[20] All models are estimated with and without employment status as a covariate. In general, this has no discernible effect on any estimates.

[21] More precisely, models that generate the predicted probabilities are linear probability models and the predicted probability is given generally by $X'_{ijqt}\beta_{97}$, where β_{97} is the vector of coefficient estimates from the cross-sectional model and X_{ijqt} represents the plausibly exogenous characteristics (i.e., age, race, education level, and marital status) of individual i residing in MSA j in quarter q of year t. We also pool all years of data and estimate these probabilities with models that include time fixed effects only. The correlation between the two measures exceeds 0.99.

[22] In particular, we chose two outcomes from each of the three broad types of health we examine (i.e., weight-related health, mental health and health behaviors).

Table 1
Allowing the impact of unemployment rate to vary by predicted employment status for selected outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment rate	0.0092 (0.0049)	0.0197 (0.0108)	0.0292 (0.0073)	0.0267 (0.0108)	−0.0164 (0.0138)	−0.0170 (0.0140)
Predicted employment status	−0.1250 (0.0440)	−0.3584 (0.1074)	−0.0544 (0.0596)	0.1126 (0.0890)	−0.2330 (0.1039)	0.5492 (0.1060)
Unemp. rate × pred. emp. status	−0.0095 (0.0061)	−0.0193 (0.0138)	−0.0229 (0.0092)	−0.0215 (0.0130)	0.0235 (0.0164)	0.0180 (0.0160)
N	26,462	26,462	26,718	26,713	26,815	23,429

Notes: Each column corresponds to a different dependent variable from one of the three broad types of health examined (i.e., weight-related health, mental health and health behaviors). Selected outcomes, in columnar order, are (1) log of body mass index, (2) an obesity indicator, (3) an indicator for whether feel hopeless at least some days, (4) an indicator for whether feel restless at least some days, (5) an indicator for daily smoking and (6) an indicator for whether an individual engages in "vigorous" exercise at least 3 days per week. With the exception of column (1), estimates are from linear probability models; probit marginal effects are similar. Models include controls for education, income relative to poverty line, age, race, marital status, and MSA, quarter and year of interview indicators. Standard errors, in parentheses, are adjusted for heteroskedasticity and correlation of observations within MSA cells.

coefficients on local unemployment rate weaken as the predicted employment value increases. Estimates in columns 5 and 6 suggest that while individuals with relatively low predicted employment values reduce daily smoking and vigorous exercise when labor market conditions worsen, this relationship diminishes in magnitude for individuals with higher values. Overall, the estimates in Table 1 imply differential impacts of local labor market conditions across the predicted employment distribution.[23]

However, since this strategy may mask important heterogeneity in the impact of labor market conditions, we split this distribution into deciles and estimate Eq. (1) separately for each of these 10 groups. Since none of the eight deciles between the 1st (lowest) and the 10th (highest) exhibit any systematic relationship between local labor market conditions and any measure of health or any health behavior, we combine individuals in these deciles into one group and report these estimates in relevant tables. As seen in Appendix A, there are substantial demographic differences across the three groups listed. In particular, those least likely to be employed (i.e., 10th percentile) are more likely to be non-white, less educated and unmarried relative to individuals in the other two groups, suggesting that this metric may well represent "exposure" to labor market conditions. Second, we estimate Eq. (1) separately by race and education level. Race groups include African-American, Hispanic and white. Since individuals with education beyond a high school diploma, but less than a bachelor's degree, are more similar to high school graduates in relevant health characteristics and behaviors, we assign individuals to two educational groups—those with less than a bachelor's degree and those with a bachelor's degree or higher level of formal education.[24] As noted earlier, allowing the effect of labor market conditions to vary by race and education level is supported by consistent evidence that the employment and earnings of lower-skilled workers are relatively more impacted by economic fluctuations.

4. Results

As discussed, empirical evidence suggests that the employment and earnings of certain groups is relatively more affected by economic fluctuations. Consistent with this general finding, we allow the estimated effect of local labor market conditions to vary across groups defined by their predicted employment status, race and educational attainment. We report estimates in a similar fashion; this section contains three sub-sections, each corresponding to one of these three delineations. In each sub-section, we present results on the impact of the local unemployment rate on weight-related health, mental health and an extensive set of health behaviors. We interpret estimates in the context of a one percentage point increase in the local unemployment rate. Given the large volume of estimates, we limit our discussion to the estimated impacts of local labor market conditions.

4.1. Estimates by predicted employment status

Tables 2A–2C are organized as follows: Column 1 represents individuals in the lowest decile of the predicted employment distribution (i.e., those least likely to be employed), Column 2 represents individuals in the highest decile of this distribution (i.e., those most likely to be employed) and Column 3 represents individuals who fall in the eight deciles between these two extremes.[25] We collapse these eight deciles into one group to facilitate the discussion of estimates and also because we detect no systematic patterns in any of the individual deciles for any outcome.

[23] Though not reported, corresponding models that interact the local unemployment rate with *actual* employment status yield results that are consistent in sign and suggest that the impact of labor market conditions on health is larger for unemployed individuals.

[24] For example, while 22% of respondents with more than a high school diploma, but less than a bachelor's degree and 23% of high school graduates report being clinically obese, only 16% of those with a bachelor's degree report likewise. Corresponding figures for cigarette smoking are, respectively, 28, 23 and 12%.

[25] Table 2B is an exception as it contains three columns for each of these three groupings for a total of nine columns. We describe its structure in detail below.

Table 2A
Estimated effect of MSA unemployment rate on weight-related outcomes, by percentile of predicted employment distribution

	10th percentile	10–90th percentile	90th percentile
Log of BMI	0.0067 (0.0048)	0.0012 (0.0016)	−0.0026 (0.0058)
BMI	0.1992 (0.1409)	0.0408 (0.0487)	−0.0480 (0.1652)
BMI between 18.5 and 25	−0.0405 (0.0158)	−0.0002 (0.0059)	0.0100 (0.0184)
BMI between 20 and 25	−0.0437 (0.0160)	0.0005 (0.0059)	0.0029 (0.0176)
BMI between 18.5 and 30	−0.0268 (0.0093)	−0.0020 (0.0051)	−0.0010 (0.0143)
BMI between 20 and 30	−0.0299 (0.0095)	−0.0013 (0.0054)	−0.0081 (0.0128)
Underweight (BMI $\leq$ 18.5)	0.0054 (0.0032)	−0.0004 (0.0006)	−0.0012 (0.0029)
Overweight (BMI $\geq$ 25)	0.0351 (0.0153)	0.0006 (0.0057)	−0.0088 (0.0184)
Obese (BMI $\geq$ 30)	0.0214 (0.0090)	0.0024 (0.0050)	0.0022 (0.0145)
BMI $\geq$ 35	0.0004 (0.0055)	−0.0004 (0.0025)	0.0049 (0.0066)
BMI $\geq$ 40	0.0002 (0.0047)	0.0008 (0.0017)	0.0008 (0.0030)
Sample size	2,648	21,129	2,685

Notes: All estimates are from linear regressions; where appropriate, probit marginal effects are similar. Models include controls for education, income relative to poverty line, age, race, marital status, employment status, and indicators for MSA, quarter and year of interview. Samples include males aged 24–59. Standard errors, in parentheses, adjusted for heteroskedasticity and correlation of observations within MSA cells.

Table 2A displays the estimated effect of local labor market conditions on weight-related health. The estimates imply that those least likely to be employed experience increases in weight when the local unemployment rate rises, though we find no evidence of a systematic relationship for the other two groups. For individuals in the lowest decile, we estimate that a one percentage point increase in the local unemployment rate leads to a weight gain of 1.34 pounds, on average. While the relevant coefficient is statistically insignificant, note that it reflects an average effect of local labor market conditions on body weight. If, for example, a rising unemployment rate leads to weight gains for some individuals and losses for others, this average effect will be attenuated. Moreover, focusing on BMI masks where in the weight distribution prospective gains or losses may be occurring.[26] As a result, it is more informative to examine clinically relevant thresholds based on BMI. We model three such thresholds: clinical measures of underweight (BMI $\leq$ 18.5), overweight (BMI $\geq$ 25) and obesity (BMI $\geq$ 30). Estimates from the first column of Table 2A suggest increases in the local unemployment rate do indeed have dual impacts on weight for this group. In particular, these estimates suggest not only increases in the fraction overweight and obese, but also increases in the fraction underweight, though the latter estimate is only marginally significant at conventional levels. Nevertheless, the directional pattern of estimates suggests differential impacts in the tails of the weight distribution. Focusing on the overweight and obese thresholds, relevant coefficients imply percentage point increases of 3.5 and 2.1, respectively. In percentage terms, these represent increases of roughly 6 and 9%. As described earlier, we also define four ranges of BMI that represent "healthy" body weights. Corresponding estimates are all negative and statistically significant at conventional levels. Focusing on the broadest of these ranges (BMI between 18.5 and 30), we find that a 1 percentage point increase in the local unemployment rate leads to roughly a 2.7 percentage point decrease in the fraction of those least likely to be employed in this range. In percentage terms, this represents a decrease of about 4%. Finally, we find no evidence of a relationship at the BMI $\geq$ 35 and 40 thresholds.

Table 2B shows the impact of local labor market conditions on responses to questions designed to assess mental health. The table is constructed as follows: the first six rows represent the questions that comprise the *K6 Scale of Non-specific Psychological Distress*, which was described in Section 2. The final row collapses responses to each of these six questions into a single metric which represents whether an individual reports *any* of the six indicated emotions at the frequencies indicated. For each question, we define three different dependent variables based on possible responses. These dependent variables correspond to columns labeled "most", "some" and "never".[27] So, for each of the three groups defined by their predicted employment status, we estimate 21 separate models. Table 2B displays estimated coefficients on local unemployment rate from each of these models.[28]

Estimates from Table 2B exhibit a consistent sign pattern. With a single exception, coefficient estimates in the "most" and "some" models are positive, while corresponding estimates in the "never" models are always negative. This pattern indicates that all three groups experience diminished mental health when the local unemployment rate increases. Closer inspection, however, shows that this pattern is most pronounced for those in the lowest predicted employment decile, where all seven coefficients in the "some" models are statistically different from zero at conventional levels.[29] Beyond statistical significance, estimates for this group are also larger in magnitude than those of the other two groups. Focusing on

[26] For example, increases in body weight among those clinically underweight likely represent different changes in weight-related health than similar gains among obese or near-obese individuals.

[27] Respectively, these represent the following frequencies: "most of the time, or more frequently", "some of the time, or more frequently", and "never".

[28] To be clear, the coefficient in the intersection of the first column and first row of Table 2B represents the estimated impact of local unemployment rate on whether an individual reports being "so sad that nothing could cheer him up" in the past 30 days "most of the time, or more frequently".

[29] In addition, three of the seven coefficients in the "most" and "never" models are statistically different from zero.

Table 2B
Estimated effect of MSA unemployment rate on mental health, by percentile of predicted employment distribution

	10th percentile			10–90th percentiles			90th percentile		
	Most	Some	Never	Most	Some	Never	Most	Some	Never
Sad	0.0152 (0.0067)	0.0340 (0.0141)	−0.0234 (0.0192)	0.0010 (0.0023)	0.0027 (0.0042)	−0.0006 (0.0070)	0.0003 (0.0026)	0.0002 (0.0074)	−0.0035 (0.0098)
Hopeless	0.0105 (0.0045)	0.0333 (0.0084)	−0.0371 (0.0120)	0.0024 (0.0018)	0.0059 (0.0031)	−0.0052 (0.0029)	0.0019 (0.0022)	0.0055 (0.0050)	−0.0086 (0.0077)
Worthless	0.0085 (0.0052)	0.0246 (0.0095)	−0.0274 (0.0112)	0.0007 (0.0019)	0.0035 (0.0021)	−0.0005 (0.0029)	0.0006 (0.0017)	0.0024 (0.0043)	−0.0063 (0.0068)
Restless	0.0039 (0.0081)	0.0350 (0.0149)	−0.0271 (0.0200)	0.0019 (0.0027)	0.0026 (0.0039)	0.0010 (0.0079)	0.0041 (0.0069)	0.0156 (0.0134)	−0.0521 (0.0143)
Nervous	0.0123 (0.0072)	0.0348 (0.0106)	−0.0402 (0.0158)	0.0012 (0.0022)	0.0048 (0.0035)	−0.0071 (0.0058)	−0.0036 (0.0042)	0.0045 (0.0126)	−0.0199 (0.0186)
Effort	0.0131 (0.0088)	0.0376 (0.0135)	−0.0236 (0.0171)	0.0042 (0.0024)	0.0040 (0.0037)	−0.0047 (0.0075)	0.0024 (0.0055)	0.0069 (0.0110)	−0.0361 (0.0143)
Any of the above	0.0250 (0.0112)	0.0401 (0.0159)	−0.0181 (0.0218)	0.0061 (0.0033)	0.0088 (0.0052)	−0.0052 (0.0106)	0.0031 (0.0090)	0.0248 (0.0156)	−0.0350 (0.0145)

Notes: All estimates are from linear probability models; probit marginal effects are similar. Models include controls for education, income relative to poverty line, age, race, marital status, employment status, and indicators for MSA, quarter and year of interview. Samples include males aged 24–59. For "10th percentile" models, sample sizes are as follows: sad = 2657, hopeless = 2659, worthless = 2654, restless = 2656, nervous = 2658, effort = 2654 and any = 2652. For "10–90th percentiles" models, corresponding sample sizes are 2700, 2700, 2700, 2700, 2700, 2698 and 2698. For "90th percentile" models, corresponding sample sizes are 21,366, 21,359, 21,364, 21,357, 21,363, 21,351 and 21,325. Standard errors adjusted for heteroskedasticity and correlation of observations within MSA cells.

Table 2C
Estimated effect of MSA unemployment rate on selected health behaviors for males, by percentile of predicted employment distribution

	10th percentile	10–90th percentiles	90th percentile
Current smoker, all days	0.0273 (0.0161)	0.0053 (0.0047)	−0.0231 (0.0091)
Current smoker, some days	0.0219 (0.0188)	0.0055 (0.0052)	−0.0160 (0.0126)
Any days with 5+ drinks	0.0058 (0.0133)	−0.0064 (0.0077)	0.0363 (0.0177)
Days with 5+ drinks	−1.605 (1.7750)	−0.1217 (0.5604)	−1.733 (1.3703)
Moderate exercise, any times per week	0.0068 (0.0131)	0.0025 (0.0081)	−0.0038 (0.0162)
Moderate exercise, 3+ times per week	0.0049 (0.0134)	−0.0024 (0.0077)	−0.0069 (0.0157)
Vigorous exercise, any times per week	−0.0089 (0.0177)	−0.0042 (0.0113)	0.0083 (0.0172)
Vigorous exercise, 3+ times per week	0.0010 (0.0162)	−0.0058 (0.0084)	0.0143 (0.0183)
Strength training, any times per week	−0.0087 (0.0191)	0.0066 (0.0051)	−0.0066 (0.0155)
Strength training, 3+ times per week	−0.0067 (0.0119)	−0.0042 (0.0048)	−0.0012 (0.0166)

Notes: All estimates are from linear regressions; where appropriate, probit marginal effects are similar. Similar to "any" and "3+ times per week" exercise models, models of "5+ times per week", though unreported, exhibit no consistent sign pattern. Models include controls for education, income relative to poverty line, age, race, marital status, employment status, and fixed effects for MSA, quarter and year of interview. Smoking equations also include state-level excise tax on cigarettes as a covariate. Samples include males aged 24–59. For the "10th percentile", sample sizes are as follows: 2685 for smoking-related outcomes, 2649 for alcohol-related outcomes, 2237 for moderate exercise-related outcomes, 2241 for vigorous exercise-related outcomes, and 2612 for strength training. For the "10–90th percentiles", corresponding sample sizes are 21,423, 21,230, 18,626, 18,749, and 21,193. For the "90th percentile", corresponding sample sizes are 2707, 2675, 2423, 2439, and 2697. Standard errors, in parentheses, are adjusted for heteroskedasticity and correlation of observations within MSA cells.

the "some" models, relevant estimates imply a 1 percentage point increase in the local unemployment rate leads to 3.4, 3.3, 2.5, 3.5, 3.5 and 3.8 percentage point increases in the fraction responding affirmatively in models of sadness, hopelessness, worthlessness, restlessness, nervousness, and feelings of effort, respectively. In percentage terms, these represent increases of 15, 24, 22, 15, 16 and 17%. However, since a one percentage point increase in the mean local unemployment rate represents an increase of between 20 and 25% relative to its overall mean, the implied "elasticities" are much smaller.

Table 2C displays results related to available health behaviors.[30] Overall, there is little evidence that the local unemployment rate impacts any of these behaviors for any of the three groups. This is especially evident for the three measures of physical exercise – moderate exercise, vigorous exercise and strength training – and their various levels of intensity—any times per week or three or more times per week.[31] One notable exception, however, is smoking behavior. Our estimates imply an increase in smoking behavior for those least likely to be employed, but reductions in smoking for those in the highest employment decile. In particular, a 1 percentage point increase in the local unemployment rate is associated with roughly a 2.7 percentage point increase for those in the lowest employment decile and a 2.3 percentage point reduction for those most likely to be employed. Respectively, these figures represent an 8% increase and a 21% decrease. We interpret this as evidence of possible heterogeneity in the impact of labor market conditions on health. Finally, note that our estimates regarding the number of days with five or more drinks, while not statistically different from zero, are negative for all three groups. These findings are consistent with Ruhm and Black (2002) who find that overall alcohol consumption is procyclical and that this observed procyclicality is driven by heavy drinkers. As reported in their Table 4, these authors find that the fraction of individuals who consumed at least 100 drinks in the past month falls when state unemployment rates rise.[32] By contrast, our finding of a statistically significant increase in the likelihood of reporting *any* days with five or more drinks for the 90th percentile is inconsistent with Ruhm and Black (2002) who find no systematic effect of economic conditions on participation in this sort of binge drinking behavior.

4.2. Estimates by race

In the following paragraphs, we describe findings from models estimated separately for African-American, Hispanic and white men. In general, the estimates imply gains in body weight and reduced mental health for African-American males in response to worsening labor market conditions, but suggest no such relationship for their Hispanic and white counterparts. In addition, there is little evidence of a systematic relationship between the local unemployment rate and the measured health behaviors of any of the three racial groups.

Table 3A presents the estimated effect of local labor market conditions on weight-related health. The general pattern of estimates implies African-American men gain weight when the local unemployment rate rises, but suggest no systematic relationship for either Hispanic or white men. As seen in Table 3A, the relevant estimate in the log BMI model (row 1) implies an average weight gain of 1.8 pounds in response to a 1 percentage point increase in local unemployment rate. In terms of distributional impacts, this average gain appears to be generated towards the right tail of the BMI distribution as a 1

[30] Note that NHIS data do not contain information on eating behavior, which is a key health behavior.
[31] Though not reported, models that examine exercise that occurs "five or more times per week" similarly show no systematic relationship.
[32] The consistency of these two findings assumes that our measure, which we think of as capturing repeated binge drinking, is positively correlated with heavy alcohol consumption as measured by Ruhm and Black (2002) who do not investigate repeated episodes of binge drinking behavior.

Table 3A
Estimated effect of MSA unemployment rate on weight-related outcomes for males, by race group

	African-American	Hispanic	White
Log of BMI	0.0085 (0.0035)	−0.0023 (0.0038)	0.0018 (0.0018)
BMI	0.2699 (0.1027)	−0.0476 (0.1117)	0.0504 (0.0526)
BMI between 18.5 and 25	−0.0190 (0.0102)	−0.0062 (0.0137)	−0.0023 (0.0078)
BMI between 20 and 25	−0.0151 (0.0102)	−0.0069 (0.0126)	−0.0033 (0.0073)
BMI between 18.5 and 30	−0.0216 (0.0092)	0.0082 (0.0124)	−0.0054 (0.0056)
BMI between 20 and 30	−0.0178 (0.0092)	0.0075 (0.0108)	−0.0064 (0.0056)
Underweight (BMI ≤ 18.5)	−0.0003 (0.0017)	0.0020 (0.0011)	0.0001 (0.0010)
Overweight (BMI ≥ 25)	0.0192 (0.0100)	0.0042 (0.0132)	0.0022 (0.0073)
Obese (BMI ≥ 30)	0.0219 (0.0091)	−0.0102 (0.0116)	0.0054 (0.0052)
BMI ≥ 35	0.0017 (0.0055)	−0.0032 (0.0066)	0.0011 (0.0031)
BMI ≥ 40	0.0017 (0.0045)	0.0021 (0.0038)	0.0002 (0.0014)
Sample size	3,998	4,091	15,810

Notes: All estimates are from linear regressions; where appropriate, probit marginal effects are similar. Models include controls for education, income relative to poverty line, age, race, marital status, employment status, and fixed effects for MSA, quarter and year of interview. Samples include males aged 24–59. Standard errors, in parentheses, are adjusted for heteroskedasticity and correlation of observations within MSA cells.

percentage point increase in the local unemployment rate leads to 1.9 and 2.2% gains in the fraction of African-American males who are clinically overweight and obese, respectively. In percentage terms, these gains are about 3 and 9%. No effect of local unemployment rate, however, is seen in the upper portions of the BMI distribution as represented by the BMI ≥ 35 and 40 thresholds. Finally, all four models of "healthy" body weight imply reductions in the fraction of African-American males in these ranges. For example, a 1 percentage point increase in the local unemployment rate is associated with nearly a 2.2 percentage point decrease in the fraction with BMI between 18.5 and 30, a decrease of nearly 3%.

Table 3B displays the estimated impact of local labor market conditions on mental health. The general pattern of estimates suggests that all three groups experience reduced mental health when the local unemployment rate rises. The pattern, however, is most pronounced for African-American and white men. With respect to African-Americans, all coefficient estimates in the "most" and "some" models are positive, while all corresponding estimates in the "never" models are negative. Focusing on the "most" models, four of the seven models exhibit estimates that are statistically different from zero at conventional levels. The last row of the first column of Table 3B implies that the fraction of African-American males who report any of the relevant six feelings "most of the time, or more frequently" increases by nearly 1.8 percentage points in response to a one percentage point increase in the local unemployment rate, which represents an increase of roughly 22%.[33] For white men, the most consistent evidence of reduced mental health is seen in the "some" models. Here, five of the seven models yield coefficient estimates that are statistically significant. While this seems inconsistent with the idea that groups whose employment is most impacted by local labor market fluctuations should have their health most impacted, further examination reveals that these particular estimates are driven by white men with relatively low educational attainment. In particular, when we divide white males into two groups according to their education, we find evidence of reduced mental health among those with less than a bachelor's degree, but weaker evidence among those with at least this amount of formal education.[34] For example, while the estimated coefficient in the "some" model where the dependent variable reflects an affirmative response to at least one of the six indicated emotions is 0.0140 ($t = 2.54$), corresponding estimates for low and high education groups are 0.0168 ($t = 2.26$) and 0.0113 ($t = 1.21$), respectively.

Table 3C presents estimates related to various health behaviors. Again, there is almost no evidence of a systematic relationship between these health behaviors and local labor market conditions. The lone exception is smoking behavior among African-American males. The relevant estimate suggests that their smoking increases in response to increases in the local unemployment rate. In particular, a 1 percentage point increase in the local unemployment rate is associated with a nearly 13% gain in the fraction of African-American males who smoke.

4.3. Estimates by education level

In this subsection, we describe findings from models estimated separately by educational attainment. As discussed in Section 2, we define two groups – those with less than a bachelor's degree and those with at least a bachelor's degree – to represent "low" and "high" education groups. While there is some evidence that more educated males gain weight when labor market conditions worsen, these gains seem to be generated by African-American males with at least a bachelor's degree. More consistent evidence suggests reduced mental health among less educated males. Once again, there is little evidence of a systematic relationship between the local unemployment rate and the health behaviors of either of these two groups.

[33] Recall that a one percentage point increase in the local unemployment rate represents between a 20 and 25% increase, making implied elasticities much smaller.

[34] In the next subsection, we estimate all models by education level and discuss relevant issues and estimates.

Table 3B
Estimated effect of MSA unemployment rate on mental health for men, by race

	African-American			Hispanic			White		
	Most	Some	Never	Most	Some	Never	Most	Some	Never
Sad	0.0066 (0.0040)	0.0059 (0.0080)	−0.0201 (0.0126)	0.0051 (0.0054)	0.0094 (0.0085)	0.0103 (0.0160)	0.0017 (0.0022)	0.0062 (0.0043)	−0.0058 (0.0062)
Hopeless	0.0106 (0.0032)	0.0077 (0.0056)	−0.0116 (0.0074)	0.0040 (0.0049)	0.0081 (0.0064)	−0.0050 (0.0081)	0.0013 (0.0018)	0.0090 (0.0033)	−0.0115 (0.0037)
Worthless	0.0054 (0.0027)	0.0089 (0.0039)	−0.0026 (0.0058)	0.0021 (0.0047)	0.0034 (0.0054)	0.0002 (0.0056)	0.0001 (0.0013)	0.0042 (0.0029)	−0.0032 (0.0036)
Restless	0.0064 (0.0069)	0.0126 (0.0092)	−0.0186 (0.0180)	0.0079 (0.0052)	0.0045 (0.0092)	0.0241 (0.0179)	0.0003 (0.0029)	0.0094 (0.0048)	−0.0157 (0.0069)
Nervous	0.0135 (0.0062)	0.0164 (0.0099)	−0.0112 (0.0133)	0.0043 (0.0047)	0.0150 (0.0075)	−0.0125 (0.0150)	−0.0021 (0.0027)	0.0060 (0.0039)	−0.0119 (0.0063)
Effort	0.0050 (0.0066)	0.0101 (0.0094)	−0.0071 (0.0156)	−0.0007 (0.0058)	0.0056 (0.0055)	0.0116 (0.0121)	0.0035 (0.0026)	0.0084 (0.0039)	−0.0156 (0.0062)
Any of the above	0.0178 (0.0084)	0.0124 (0.0111)	−0.0181 (0.0208)	0.0126 (0.0073)	0.0142 (0.0114)	0.0041 (0.0222)	0.0014 (0.0042)	0.0140 (0.0057)	−0.0157 (0.0080)

Notes: All estimates are from linear probability models; probit marginal effects are similar. Models include controls for education, income relative to poverty line, age, race, marital status, employment status, and indicators for MSA, quarter and year of interview. Samples include males aged 24–59. For "African-American" models, sample sizes are as follows: sad = 4032, hopeless = 4033, worthless = 4032, restless = 4031, nervous = 4031, effort = 4029 and any = 4023. For "Hispanic" models, corresponding sample sizes are 4169, 4170, 4168, 4168, 4171, 4167 and 4167. For "White" models, corresponding sample sizes are 15,926, 15,922, 15,924, 15,924, 15,925, 15,918 and 15,914. Standard errors, in parentheses, are adjusted for heteroskedasticity and correlation of observations within MSA cells.

Table 3C
Estimated effect of MSA unemployment rate on various health behaviors for males, by race

	African-American	Hispanic	White
Current smoker, all days	0.0300 (0.0111)	0.0003 (0.0083)	−0.0044 (0.0056)
Current smoker, some days	0.0328 (0.0105)	−0.0099 (0.0098)	−0.0026 (0.0062)
Any days with 5+ drinks	−0.0054 (0.0117)	0.0030 (0.0099)	0.0003 (0.0077)
Days with 5+ drinks	0.7797 (1.9285)	−0.6479 (0.8988)	−0.7148 (0.6628)
Moderate exercise, any times per week	0.0056 (0.0124)	−0.0182 (0.0163)	0.0091 (0.0084)
Moderate exercise, 3+ times per week	0.0048 (0.0106)	−0.0169 (0.0156)	−0.0012 (0.0078)
Vigorous exercise, any times per week	−0.0252 (0.0189)	−0.0106 (0.0168)	0.0010 (0.0096)
Vigorous exercise, 3+ times per week	−0.0243 (0.0155)	−0.0076 (0.0105)	0.0019 (0.0080)
Strength training, any times per week	0.0051 (0.0138)	−0.0032 (0.0106)	0.0035 (0.0063)
Strength training, 3+ times per week	−0.0033 (0.0101)	−0.0070 (0.0065)	−0.0039 (0.0061)

Notes: All estimates are from linear regressions; where appropriate, probit marginal effects are similar. Similar to "any" and "3+ times per week" exercise models, models of "5+ times per week", though unreported, exhibit no consistent sign pattern. Models include controls for education, income relative to poverty line, age, marital status, employment status, and fixed effects for MSA, quarter and year of interview. Smoking equations also include state-level excise tax on cigarettes as a covariate. Samples include males aged 24–59. For African-Americans, sample sizes are as follows: 4041 for smoking-related outcomes, 3992 for alcohol-related outcomes, 3497 for moderate exercise-related outcomes, 3513 for vigorous exercise-related outcomes, and 3970 for strength training. For Hispanics, corresponding sample sizes are 4174, 4154, 3638, 3643, and 4147. For Whites, corresponding sample sizes are 15,995, 15,822, 13,863, 13,964, and 15,819. Standard errors adjusted for non-independence of observations within MSAs are in parentheses.

Table 4A
Estimated effect of MSA unemployment rate on weight-related outcomes for males, by education level

	Less than BS	BS or higher
Log of BMI	0.0001 (0.0017)	0.0050 (0.0026)
BMI	0.0120 (0.0555)	0.1480 (0.0732)
BMI between 18.5 and 25	−0.0003 (0.0056)	−0.0126 (0.0103)
BMI between 20 and 25	−0.0001 (0.0054)	−0.0138 (0.0101)
BMI between 18.5 and 30	−0.0008 (0.0050)	−0.0106 (0.0078)
BMI between 20 and 30	−0.0006 (0.0054)	−0.0119 (0.0072)
Underweight (BMI $\leq$ 18.5)	0.0002 (0.0007)	−0.0007 (0.0013)
Overweight (BMI $\geq$ 25)	0.0001 (0.0053)	0.0133 (0.0102)
Obese (BMI $\geq$ 30)	0.0007 (0.0049)	0.0114 (0.0075)
BMI $\geq$ 35	−0.0023 (0.0025)	0.0049 (0.0036)
BMI $\geq$ 40	0.0004 (0.0023)	0.0015 (0.0016)
Sample size	17,951	8,307

Notes: All estimates are from linear regressions; where appropriate, probit marginal effects are similar. Models include controls for education (relevant categories only), income relative to poverty line, age, race, marital status, employment status, and fixed effects for MSA, quarter and year of interview. Samples include males aged 24–59. Standard errors, in parentheses, are adjusted for heteroskedasticity and correlation of observations within MSA cells.

Table 4A displays estimates of the impact of local labor market conditions on weight-related health. The general pattern of estimates suggests that relatively more educated men gain weight when the local unemployment rate rises, while there is no such evidence for men with less than a bachelor's degree. The relevant coefficient estimate in Table 4A implies an average weight gain of about one pound when the local unemployment rate increases by one percentage point. Note, however, that the estimated effect appears to be driven by African-American men in the high education group. When these models are estimated separately by race, the corresponding coefficients are 0.0159 ($t = 1.94$), 0.0046 ($t = 0.26$) and 0.0039 ($t = 1.32$) for highly educated African-American, Hispanic and white men in the log BMI specification. Estimates for other measures of weight-related health show a similar pattern, though none are estimated precisely.

Table 4B shows the estimated effect of local labor market conditions on mental health. A consistent sign pattern is evident as coefficient estimates in all but two of the "most" and "some" models are positive, while all corresponding estimates in the "never" models are negative. This pattern suggests that both education groups experience reduced mental health when the local unemployment rate rises. Note, however, that the pattern is more pronounced for individuals with less than a bachelor's degree, where five of the seven "some" models yield estimates statistically different from zero at conventional levels.[35] Beyond precision, estimated coefficients for less educated men are consistently larger than those of their more educated counterparts. Focusing on the "some" models, relevant estimates imply a one percentage point increase in the local unemployment rate leads to 0.7, 1.3, 0.8, 0.9, 1.4 and 1.1 percentage point gains in the fraction reporting feelings of sadness, hopelessness, worthlessness, restlessness, nervousness and effort, respectively, "some of the time, or more frequently". In percentage terms, these represent increases of about 6, 21, 16, 5, 10 and 8%, respectively. By contrast, while there is some evidence of a procyclical relationship for better-educated individuals (e.g., the sign pattern of the coefficients), the implied effects are smaller in magnitude and less precisely estimated than for their less-educated counterparts.

[35] In addition, three of the seven coefficients in the "most" and two of the seven coefficients in the "never" models are statistically significant.

Table 4B
Estimated effect of MSA unemployment rate on mental health for males, by education level

	Less than bachelor's degree			Bachelor's degree or higher		
	Most	Some	Never	Most	Some	Never
Sad	0.0038 (0.0027)	0.0070 (0.0050)	−0.0016 (0.0075)	0.0010 (0.0024)	0.0069 (0.0039)	−0.0104 (0.0083)
Hopeless	0.0052 (0.0018)	0.0128 (0.0033)	−0.0213 (0.0035)	0.0014 (0.0017)	0.0049 (0.0028)	−0.0073 (0.0049)
Worthless	0.0025 (0.0019)	0.0076 (0.0031)	−0.0047 (0.0032)	0.0016 (0.0020)	0.0056 (0.0032)	−0.0052 (0.0048)
Restless	0.0032 (0.0033)	0.0094 (0.0050)	−0.0058 (0.0089)	0.0029 (0.0028)	0.0067 (0.0056)	−0.0072 (0.0099)
Nervous	0.0050 (0.0026)	0.0136 (0.0040)	−0.0120 (0.0056)	−0.0029 (0.0027)	−0.0003 (0.0056)	−0.0105 (0.0083)
Effort	0.0053 (0.0029)	0.0106 (0.0048)	−0.0089 (0.0070)	0.0073 (0.0034)	0.0080 (0.0058)	−0.0136 (0.0096)
Any of the above	0.0087 (0.0038)	0.0137 (0.0055)	−0.0096 (0.0100)	0.0039 (0.0042)	0.0108 (0.0082)	−0.0093 (0.0121)

Notes: All estimates are from linear probability models; probit marginal effects are similar. Models include controls for education (relevant categories only), income relative to poverty line, age, race, marital status, employment status, and indicators for MSA, quarter and year of interview. Samples include males aged 24–59. For "less than bachelor's degree" models, sample sizes are as follows: sad = 8375, hopeless = 8377, worthless = 8374, restless = 8374, nervous = 8374, effort = 8372 and any = 8368. For "bachelor's degree or higher" models, corresponding sample sizes are 18,126, 18,119, 18,121, 18,117, 18,124, 18,110 and 18,096. Standard errors, in parentheses, are adjusted for heteroskedasticity and correlation of observations within MSA cells.

Table 4C
Estimated effect of MSA unemployment rate on various health behaviors, by education level

	Less than a BS	BS or higher
Current smoker, all days	0.0037 (0.0052)	0.0066 (0.0066)
Current smoker, some days	0.0040 (0.0061)	0.0072 (0.0066)
Any days with 5+ drinks	−0.0044 (0.0068)	0.0114 (0.0096)
Days with 5+ drinks	−0.8088 (0.7527)	0.4465 (0.5112)
Moderate exercise, any times per week	0.0018 (0.0089)	0.0013 (0.0097)
Moderate exercise, 3+ times per week	0.0008 (0.0087)	−0.0106 (0.0085)
Vigorous exercise, any times per week	−0.0041 (0.0128)	−0.0043 (0.0088)
Vigorous exercise, 3+ times per week	0.0008 (0.0106)	−0.0104 (0.0093)
Strength training, any times per week	0.0046 (0.0074)	0.0041 (0.0070)
Strength training, 3+ times per week	0.0004 (0.0058)	−0.0103 (0.0074)

Notes: All estimates are from linear regressions; where appropriate, probit marginal effects are similar. Similar to "any" and "3+ times per week" exercise models, models of "5+ times per week", though unreported, exhibit no consistent sign pattern. Models include controls for education (relevant categories only), income relative to poverty line, age, marital status, employment status, and indicators for MSA, quarter and year of interview. Smoking equations also include state-level excise tax on cigarettes as a covariate. Samples include males aged 24–59. For those with less than a BS, sample sizes are as follows: 8403 for smoking-related outcomes, 8327 for alcohol-related outcomes, 7405 for moderate exercise-related outcomes, 7457 for vigorous exercise-related outcomes, and 8349 for strength training. For those with a BS or higher, corresponding sample sizes are 18,189, 17909, 15,688, 15,778, and 17,940. Standard errors, in parentheses, are adjusted for heteroskedasticity and correlation of observations within MSA cells.

Finally, Table 4C shows estimates related to health behaviors by education group. Consistent with earlier estimates, there is no systematic evidence of a relationship between the set of health behaviors examined and the local unemployment rate. In general, this is a consistent finding across all groups examined in this paper.

5. Discussion

As outlined in the previous section, we find systematic evidence of procyclical relationships for weight-related health and, especially, mental health for a sample of men residing in the 58 largest MSAs in the U.S. These relationships are most pronounced for individuals in the lowest predicted employment decile and African-Americans. In what follows, we discuss our most notable findings, paying particular attention to why our findings are confined largely to groups with relatively low socioeconomic status (SES).

In general, economists conceptualize body weight in terms of a simple production function where changes in weight are determined by the difference between the intake and expenditure of calories (c.f., Philipson and Posner, 1999). As noted, we find evidence of body weight increases in response to rising unemployment rates for those least likely to be employed and African-Americans. Coupled with our finding of no systematic link between local unemployment rates and physical exercise, increased caloric intake is a natural implication. While this is plausible, perhaps through increased consumption of lower quality (e.g., calorie dense) foods, the nature of the production function provides an alternative explanation.[36] For example, evidence from the neurosciences suggests that prolonged psychosocial stress, in conjunction with certain hormonal

[36] While we cannot explicitly test them, there are many reasons why calorie consumption may increase. For example, Laitinen et al. (2002) find that stress-driven eaters tend to prefer high-fat foods when given a choice and anecdotal evidence suggests that individuals often turn to high-calorie "comfort" foods when experiencing stress. Finally, individuals affected negatively by labor market fluctuations may substitute into such lower quality foods (e.g., calorie-dense prepared foods vs. vegetables) to save money.

responses, leads to increased accumulation of body fat in some individuals. If there is a connection between labor market fluctuations and stress, then the former may affect weight independent of calories consumed or directly expended (e.g., via exercise). In terms of the two general explanations for cyclicality in health, our weight-related findings are inconsistent with the time-use hypothesis which, generally speaking, argues that the production of weight-related health should increase when labor market conditions worsen.[37] By contrast, the reductions in mental health we find, among these same groups, are perhaps suggestive of an explanation closer to the economic stress hypothesis. However, the fact that we observe weight gains among those whose mental health is sensitive to economic conditions does not necessarily imply that the economic stress hypothesis explains these weight gains.

Our finding that mental health is procyclical in nature is seen somewhat broadly, but is most pronounced for groups whose employment prospects have been found by others to be most impacted by labor market fluctuations. In particular, we find consistent evidence of reduced mental health for those least likely to be employed, African-Americans and individuals with less than a bachelor's degree. Moreover, relevant effects for these groups are seen consistently at the "most of the time, or more often" threshold, suggesting potentially substantial effects on mental health. These estimates are consistent with a relatively small amount of work that suggests mental health is procyclical. Relative to our weight-related findings, this evidence appears more consistent with the economic stress hypothesis since time is likely not as prominent an input in the production of mental, as opposed to, physical health. In essence, the associated models are likely more direct tests of this explanation.

We turn now to reasons why our effects are confined to low SES groups. As already suggested, actual exposure to labor market conditions, in terms of employment and earnings, may explain this pattern. For example, individuals with low employment probabilities, African-Americans and those with relatively low levels of formal education may be more likely to experience direct consequences of fluctuating economic conditions, relative to the general population. In particular, such individuals may experience actual changes in income, as suggested by previous work. If so, this provides a possible pathway for the health effects we observe. We believe that this explanation, while not directly testable with our data, is plausible since our most pronounced findings are for groups which previous research suggests are most impacted by labor market fluctuations in terms of employment and earnings.

In addition to reductions in absolute income, individuals in these groups may experience declines in their *relative* income, as a result of fluctuating labor market conditions.[38] Recent work by Eibner and Evans (2005) shows that greater relative deprivation, in the sense of Yitzhaki (1979), is linked to a host of poor health indicators, including increased body mass index, and ultimately mortality, in a sample of males.[39] In particular, the authors extend the concept of relative deprivation from one's relative income ranking within a particular reference group, to account for the average income of those with higher incomes. To the extent that changing labor market conditions do indeed have relatively larger income effects for these individuals, this provides additional support for the plausibility of our general finding that health effects are confined to lower SES groups.[40]

Finally, there is increasing evidence from the neurosciences that individuals with lower socioeconomic status have elevated "allostatic loads".[41] Allostatic load refers to the cumulative price the body pays for repeated exposure to adverse psychosocial situations. Generally, it is thought to involve the presence of too much stress, coupled with inefficient operation of the stress hormone response system, over prolonged periods of time. More specifically, stressful events are thought to trigger hormonal responses that, while protective in the short-run, can cause harm when they remain active for longer periods. Such a situation may make the health of certain individuals particularly susceptible to increased levels of stress. In the present case, a relevant example involves elevated levels of cortisol in the body, brought on by periods of prolonged stress.[42] An elevated level of cortisol, in turn, reduces insulin's ability to process glucose (sometimes referred to as "insulin resistance") and, as a result, promotes the accumulation of body fat.[43] As noted, our weight-related findings are confined to low SES groups. We also find evidence that the same groups report greater "restlessness" and "nervousness" with worsening labor market conditions, suggesting increases in stress. If individuals in these groups are prone to already high allostatic loads, this provides additional support for our weight-related health findings.

[37] That said, additional time may be allocated to sedentary activities like television watching or job search.

[38] Greater relative deprivation among these groups, in response to changing labor market conditions, depends on them experiencing larger income effects, relative to their higher SES counterparts, as is suggested by previous research (c.f., Hoynes, 2000).

[39] The authors did not examine outcomes or measures related to mental health.

[40] This connection also depends on the scope of the relevant reference group. If it is comprised of very similar individuals, there would be little impact on relative deprivation. By contrast, the impact would be greater, the wider the reference group. Eibner and Evans (2005) have a nice discussion of the issues involved, but note that this remains an open question.

[41] This paragraph draws heavily on McEwen (2000) and Bjorntorp and Rosmond (2000).

[42] Cortisol, a glucocortoid, is a particular stress hormone produced by the adrenal glands. Production of cortisol is regulated by the pituitary gland, via adrenocorticotropic hormone (ACTH).

[43] Moreover, researchers have found that elevated levels of glucocortoids increase food consumption in rodents (c.f., Dallman et al., 2003; Pecoraro et al., 2004). In a more recent study, researchers attempted to understand the possible differential impact of chronic stress on the weight of rodents based on their social position. Rodents were assigned to three groups—dominant, subordinate and a control group. While both dominant and subordinate rodents ate more than the control group when stressed, only the subordinate group gained weight. The authors found that this was due to decreased caloric efficiency in the subordinate rodents, relative to their dominant counterparts (Moles et al., 2006).

6. Conclusions

In this paper, we present systematic evidence of procyclical relationships for weight-related health and, especially, mental health for a sample of men living in the 58 largest MSAs in the U.S. We find these relationships are most pronounced for groups previously found to be most affected by changing labor market conditions. In particular, our evidence is most consistent for those least likely to be employed and African-Americans. As discussed, our findings have similarities to and differences with existing work, which suggests that physical health is countercyclical in nature while mental health is procyclical. Given the consistency of the findings regarding mental health, a deeper understanding of the long-run implications of changes in mental health is appropriate. For example, how long does the detrimental effect of worsening labor market conditions reduce mental health? Moreover, do such changes in mental health have implications for longer-run physical health or other non-health issues such as homelessness, illegal drug use or criminal activity, all of which have been linked to mental illness? To the extent possible, such extensions should be examined in future related work.

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Appendix A. Selected means and standard deviations by percentile of predicted employment distribution

	10th percentile	10–90th percentiles	90th percentile
Employed	0.587 (0.492)	0.907 (0.290)	0.976 (0.153)
Non-white	0.437 (0.496)	0.243 (0.429)	0.093 (0.290)
Less than high school	0.496 (0.500)	0.160 (0.367)	0.011 (0.104)
High school or less	0.703 (0.457)	0.396 (0.489)	0.128 (0.334)
Bachelor's degree or higher	0.096 (0.295)	0.301 (0.459)	0.607 (0.488)
Married	0.326 (0.469)	0.500 (0.500)	0.943 (0.232)
Living with partner	0.064 (0.244)	0.061 (0.239)	0.032 (0.176)
Separated or divorced	0.210 (0.407)	0.160 (0.367)	0.015 (0.120)
Never married	0.359 (0.480)	0.264 (0.441)	0.010 (0.101)
Sample size	2,715	21,728	2,715

Notes: The column labeled "10th percentile" reflects those in the lowest decile of the predicted employment status distribution, "90th percentile" reflects individuals in the highest decile and "10–90th percentile" reflects those in the intermediate eight deciles.

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