International Scholarly Research Network
ISRN Public Health
Volume 2012, Article ID 318610, 7 pages
doi:10.5402/2012/318610

Research Article

Local Labor Market Fluctuations and Physical Activity among Adults in the United States, 1990–2009

Ruopeng An[1] and Junyi Liu[2, 3]

[1] *Pardee RAND Graduate School, RAND Corporation, 1776 Main Street, Santa Monica, California, CA 90407, USA*
[2] *Economics Department, Loyola Marymount University, Los Angeles, CA 90045, USA*
[3] *Economics Department, Indiana University, Bloomington, IN 47405, USA*

Correspondence should be addressed to Ruopeng An, ran@rand.org

Received 9 September 2012; Accepted 26 September 2012

Academic Editors: E. Alderete, E. Lazcano-Ponce, and N. Wedderkopp

Being physically active is a key health promotion strategy. The late-2000s economic downturn, labeled the "Great Recession," could have profound impact on individuals' health behaviors including engagement in physical activity. We investigated the relationship between local labor market fluctuations and physical activity among adults 18 years and older in the United States by linking individual-level data in the Behavioral Risk Factor Surveillance System 1990–2009 waves to unemployment rate data by residential county and survey month/year. The association between labor market fluctuations and physical activity was examined in multivariate regressions with county and month/year fixed effects. Deteriorating labor market conditions were found to predict decreases in physical activity—a one percentage point increase in monthly county unemployment rate was on average associated with a reduction in monthly moderate-intensity physical activity of 0.18 hours. There was some preliminary evidence on the heterogeneous responses of physical activity to local labor market fluctuations across age and income groups and races/ethnicities. Findings of this study suggest special attentions to be paid to the potential detrimental impact of major recessions on physical activity. This correlational study has design and measurement limitations. Future research with longitudinal or experimental study design is warranted.

1. Introduction

Being physically active is essential to improving overall health and fitness and preventing adverse health outcomes and diseases, such as coronary heart disease, stroke, type 2 diabetes, osteoporosis, and depression [1]. The late-2000s economic downturn, labeled the "Great Recession", could have profound impact on individuals' health behaviors including engagement in physical activity. Such concerns are highlighted in recent medical journal editorials: "Job insecurity, unemployment, and deterioration of working conditions are all potentially harmful to population health and require urgent attention" [2]; "The economic downturn can be expected to reduce nutrition quality and physical activity, worsening obesity prevalence when society is least able to bear the escalating financial burden" [3].

A number of hypotheses have proposed causal links between economic conditions and physical activity. One popular hypothesis among economists is related to time use—a reduction of hourly wages during recessions (or even the absence of paid work options) lowers the opportunity cost of time, creating incentives for people to increase leisure-time activities including physical activity. In contrast, researchers in other disciplines emphasize that people may undergo excessive financial and psychological stress during recessions, which contributes to the development of a sedentary lifestyle and decreased level of physical activity [4]. Another explanation relates to the built and social neighborhood environment—as neighborhoods deteriorate during recessions (e.g., increased foreclosed homes, undermaintained recreation facilities, and street crimes), residents are discouraged from engaging in physical activity [5, 6].

In contrast to the public attention and hypothetical pathways that link economic conditions to health behaviors and outcomes, existing studies on the impact of labor market fluctuations on physical activity remain sparse and inconclusive. Using individual-level data from the Behavioral Risk Factor Surveillance System (BRFSS) 1987–2000 waves, Ruhm [7] documented an increase in physical activity when state labor market conditions worsened—a one percentage point increase in state unemployment rate predicted a reduction in the prevalence of physical inactivity by 0.7%. Conversely, Charles and DeCicca [8] used the National Health Interview Survey 1997–2001 waves and reported a lack of association between metropolitan statistical area unemployment rate and physical activity among respondents at high risk of job loss. Nicholson and Simon [9] used the Gallup Healthways Wellbeing Survey 2008–2010 waves to study the impact of the Great Recession on physical activity. An increase in state or county unemployment rate predicted a decrease in the number of physically active days among survey participants. Using the American Time Use Survey 2003–2010 waves, Colman and Dave [10] reported a decline in total physical exertion when state or core-based statistical area unemployment rate rose, and the effect appeared largest among less educated males.

In this study, we examined the association between local labor market conditions and physical activity, by linking individual-level data in the BRFSS 1990–2009 waves to monthly county unemployment rate. We contributed to the literature by adding a new data point with finer geographical resolution (i.e., county) and a large nationally representative sample—compared to state unemployment rate, county unemployment rate tends to better capture local labor market fluctuations—and we analyzed data on about 2 million respondents with a time span of 20 years covering the Great Recession.

2. Methods

2.1. Study Sample. Individual-level data came from the BRFSS 1990–2009 waves. Established in 1984 by the Centers for Disease Control and Prevention, BRFSS is the world's largest on-going telephone health survey system, tracking health conditions and risk behaviors of adults 18 years and older in all US states. In the 20 waves from 1990 to 2009, questions on physical activity were administered for every year except 2002, 2004, 2006, and 2008, involving a total sample of 2,416,224 respondents.

2.2. Variable Constructions. The primary dependent variable is a respondent's total hours of moderate-intensity (i.e., moderate and vigorous) physical activity in the survey month. It was calculated from the responses to the following questions: "Now, thinking about the moderate activities you do in a usual week, such as brisk walking, bicycling, vacuuming, gardening, or anything else that causes some increase in breathing or heart rate, how many days per week do you do these moderate activities?"; "On days when you do moderate activities, how much total time per day do you spend doing these activities?"; "Now, thinking about the vigorous activities you do in a usual week, such as running, aerobics, heavy yard work, or anything else that causes large increases in breathing or heart rate, how many days per week do you do these vigorous activities?", "On days when you do vigorous activities, how much total time per day do you spend doing these activities?" The above question items have been administered in the BRFSS since 2000, while corresponding questions from 1990 to 1999 slightly differed. Differences in question wording were accounted for using year (i.e., survey wave) fixed effects.

We classified exercisers based on their self-reported physical activity level. A dichotomous variable for "existing exerciser" was constructed for anyone who did any moderate or vigorous exercise in the survey month. The 2008 Physical Activity Guidelines for Americans recommends at least 150 minutes (i.e., 2.5 hours) a week of moderate-intensity physical activity in order to achieve health benefits [1]. We thus defined "regular exerciser" as someone reporting 10 or more hours of physical activity per month.

Our primary explanatory variable is the monthly county unemployment rate. We merged the unemployment rate from the US Department of Labor Bureau of Labor Statistics to BRFSS individual-level data by the respondent's residential county and survey month/year.

In subgroup analysis, county level income from the US Department of Commerce Bureau of Economic Analysis is used. The income data is available from 1990 to 2009 and converted to the 2009 US dollar using the all-items consumer price index from the US Bureau of Labor Statistics. It can be debated whether an individual or a contextual income measure is more appropriate as they have different interpretations. However, we do not have much choice here given the poor quality of individual measure in the BRFSS (e.g., very large income intervals, grouping most of the population at the top), so we choose to use county annual per capita income as in earlier studies [7, 11, 12].

In multivariate analysis, we controlled for the following individual characteristics: gender; age (age in years and age squared); race/ethnicity (dichotomous variables for African American, Hispanic, Asian or Pacific Islander, and other race/multirace, in comparison to White); education (dichotomous variables for high school graduate, education higher than high school but lower than college, and college graduate or higher, in comparison to education lower than high school); marital status (dichotomous variables for divorced/widowed/separated and never married, in comparison to married). Arguably, an essential mechanism that recessions may affect people's physical activity through is individual job loss. Following Ruhm [7], we did not control for individual employment status because (1) we intended to estimate the overall impact of local labor market conditions, and (2) individual employment status, as a variable subject to personal preference, could be endogenous in our estimation.

2.3. Statistical Analysis. We used the following multivariate regression model with county, year, and month fixed effects to estimate the relationship between local labor market conditions and physical activity:

$$P_{icmy} = T_{icmy}\beta + X_{icmy}\lambda + \alpha_c + \gamma_m + \mu_y + \varepsilon_{icmy}. \quad (1)$$

In (1), P is a measure of physical activity for individual i residing in county c interviewed in month m of year y; T is the key explanatory variable (i.e., monthly county unemployment rate); X is a vector of individual characteristics (i.e., age, gender, race/ethnicity, education, and marital status); α, γ, and μ are the unobserved determinants of physical activity associated with county, survey month, and year; ε is a disturbance term. The county fixed effects control for time-invariant determinants that differ across counties, the month fixed effects hold constant the seasonal variations in physical activity, and the year fixed effects account for the secular trends of physical activity (as well as the changes in question wording before and after 2000) that may confound with our estimated effect of local labor market conditions on physical activity β.

To assess the heterogeneous responses of physical activity to local labor market fluctuations, we conducted subgroup analysis by estimating (1) for each gender, age group, race/ethnicity, and income group in separate regressions.

Eicker-Huber-White sandwich estimator was used to calculate standard errors clustered at county level to account for the within-county serial correlations that may downward bias the standard errors of estimates [13]. Sampling weights reduce estimation efficiency [14, 15]. We therefore reported unweighted models, although we used the BRFSS final sampling weights for descriptive statistics. As a sensitivity analysis, we also repeated the regression models using the BRFSS final sampling weights. We obtained similar quantitative results as when using the unweighted models.

Approximately a quarter of the sample were missing their residential county identifier due to the BRFSS confidentiality policy to mask residents in less populated areas, resulting in an effective sample of 1,805,997 respondents residing in 2,623 US counties. State identifier was complete in the sample. As a sensitivity analysis, we replaced each missing county identifier with the county's corresponding state unemployment rate and reconducted the analysis. We obtained very similar results as when using the effective sample.

3. Results

Table 1 shows descriptive statistics of the variables included in multivariate analysis. During the study period from 1990 to 2009, American adults on average spent 20 hours per month on moderate-intensity physical activity. Even so, 29% of the population did not engage in any physical activity, and about one-third (32%) of existing exercisers failed to meet the 10 hours per month of moderate-intensity physical activity recommended by the US physical activity guidelines.

Table 2 shows the estimated relationship between local labor market fluctuations and physical activity. Deteriorating labor market conditions were found to predict decreases in physical activity in the population. A one percentage point increase in monthly county unemployment rate was associated with a reduction in monthly moderate-intensity physical activity of 0.18 hours. The decline appeared to concentrate among existing exercisers, while the influence of labor market conditions on the probability of any engagement in physical activity seemed insignificant. In the model with the dichotomous variable denoting any physical activity as the dependent variable, the coefficient of monthly county unemployment rate is statistically indifferent from zero. Conversely, among existing exercisers, a one percentage point increase in unemployment rate predicts decrease in physical activity by 0.25 hours per month. The impact of local labor market fluctuations on regular exercisers (0.26 hours per month) appeared similar as that on existing exercisers.

Table 3 reports the results of subgroup analysis by gender, age, race/ethnicity, and income. There was no noticeable difference between genders in the response of physical activity to local labor market conditions. Physical activity among all age groups decreased with an increase in unemployment rate. This effect was most pronounced in people 65 years and older. Some heterogeneity across races/ethnicities appeared to be present. Physical activity among other race or multirace was found to be most responsive to labor market fluctuations, followed by that among non-Hispanic White, while that among African American and Hispanic was not statistically significant. Asian remained the only minority group whose time spent on physical activity increased during economic downturns. A one percentage point increase in monthly county unemployment rate predicted an additional 0.35 hours per month of physical activity and an increase in the probability of being physically active by 0.6 percentage point among the Asian population. Compared to their richer counterparts, physical activities among individuals living in the poorest counties (county annual per capita income less than $25,000) seemed to be negatively impacted the most by economic downturns.

The influence of local labor market conditions on physical activity may not be fully simultaneous. We explored the potential time lag by regressing concurrent physical activity on past county monthly unemployment rate. As Table 4 shows, earlier labor market fluctuations were found to be negatively associated with contemporary physical activity level, but the association largely faded out in about three months.

4. Discussion

In this study, we investigated the relationship between local labor market conditions and physical activity by linking individual-level data in the BRFSS 1990–2009 waves to monthly county unemployment rate. Deteriorating labor market conditions were found to predict decreases in physical activity in the population. There was also some preliminary evidence on the heterogeneous responses of physical activity to local labor market fluctuations across age and income groups and races/ethnicities.

This correlational study has important limitations. The most salient one has to do with the cross-sectional nature of the survey data. We defined existing exerciser, regular exerciser, and physical inactivity purely based on the self-reported hours of physical activity in a typical week close to the survey date. These cross-sectional measures are rough and not able to (1) correctly classify those who regularly engaged in physical activity but accidentally remained inactive during the period close to the survey date, (2) capture any weekly variations in physical activity within the survey month, or (3) identify within-individual behavioral changes over time. In addition, we were restricted to the investigation

Table 1: Descriptive statistics of the BRFSS sample and county unemployment rate.

Variable	Attribute	Unweighted mean	Weighted mean
Physical activity			
Hours of physical activity in the survey month	Continuous	19.65 (33.69)	20.00 (34.76)
Any physical activity in the survey month	Dichotomous	0.70 (0.46)	0.71 (0.45)
Gender			
Male	Dichotomous	0.40 (0.49)	0.48 (0.50)
Age			
Age in years	Continuous	49.85 (17.43)	44.78 (17.47)
Age in years squared	Continuous	2789.10 (1828.38)	2310.28 (1731.51)
Race/ethnicity			
White (non-Hispanic)	Dichotomous	0.80 (0.40)	0.74 (0.44)
African American (non-Hispanic)	Dichotomous	0.08 (0.27)	0.09 (0.29)
Asian or Pacific Islander (non-Hispanic)	Dichotomous	0.02 (0.14)	0.03 (0.16)
Other race or multirace (non-Hispanic)	Dichotomous	0.03 (0.17)	0.02 (0.15)
Hispanic	Dichotomous	0.07 (0.26)	0.11 (0.32)
Education			
Education lower than high school	Dichotomous	0.11 (0.32)	0.13 (0.34)
High school graduate	Dichotomous	0.31 (0.46)	0.31 (0.46)
Education higher than high school lower than college	Dichotomous	0.27 (0.44)	0.26 (0.44)
College graduate or higher	Dichotomous	0.31 (0.46)	0.29 (0.45)
Marital status			
Married	Dichotomous	0.58 (0.49)	0.63 (0.48)
Divorced or widowed or separated	Dichotomous	0.27 (0.45)	0.18 (0.38)
Never married	Dichotomous	0.15 (0.35)	0.19 (0.39)
Local labor market condition			
Monthly county unemployment rate	Continuous	5.71 (2.74)	5.89 (2.79)

Note. (a) Individual data (N = 1,805,997) is from Behavioral Risk Factor Surveillance System (BRFSS) 1990–2009 waves. (b) Monthly county unemployment rate is from US Department of Labor Bureau of Labor Statistics. (c) Variable mean is weighted using BRFSS final sampling weights. (d) Standard deviation is in parentheses.

Table 2: Estimated associations between local labor market conditions and physical activity, 1990–2009.

	Hours of physical activity per month	Any physical activity in the survey month	Hours of physical activity per month among existing exercisers (hours > 0)	Hours of physical activity per month among regular exercisers (hours ≥ 10)
Monthly county unemployment rate	−0.1849***	0.0002	−0.2473***	−0.2582***
	(0.0335)	(0.0005)	(0.0423)	(0.0486)
Sample size	1,805,997	1,805,997	1,300,052	918,211

Note. (a) Individual data is from Behavioral Risk Factor Surveillance System 1990–2009 waves. (b) Monthly county unemployment rate is from US Department of Labor Bureau of Labor Statistics. (c) The treatment variable in all models is monthly county unemployment rate. (d) All models are OLS and control for individual characteristics (i.e., gender, age, race/ethnicity, education, and marital status) and county and year/month fixed effects. (e) Estimated standard error of coefficient is in parentheses. Eicker-Huber-White sandwich estimator is used to calculate standard error clustered at county level. (f) $^{*}P < 0.05$, $^{**}P < 0.01$, $^{***}P < 0.001$.

of the overall relationship between local labor market conditions and physical activity because the BRFSS did not collect sufficient data to support an examination of specific pathways: income only available in broad brackets, limited mental health measures, and lack of information on residential neighborhood environment.

Measurement errors tend to be present for both the outcome variables (i.e., monthly hours of physical activity and the dichotomous variable for any physical activity) and the treatment variable (i.e., monthly county unemployment rate). Monthly hours of physical activity was calculated from self-reported frequency and duration of physical activity in the BRFSS. Numerous studies show that self-reported physical activity is subject to measurement error, and the direction of bias (i.e., overstatement or understatement of the true level of physical activity) is uncertain [16]. Measures on physical activity in the BRFSS were limited to leisure-time exercise, while other types of physical activity, such as work-related exertion or housework were not surveyed. Questions related to physical activity were somewhat inconsistent before 2000, and they were not administered for 2002, 2004, 2006, and 2008.

Table 3: Estimated associations between local labor market conditions and physical activity by gender, age group, and race/ethnicity, 1990–2009.

	Hours of physical activity per month	Any physical activity in the survey month	Hours of physical activity per month among existing exercisers (hours > 0)	Hours of physical activity per month among regular exercisers (hours ≥ 10)
Gender				
Male	−0.1895***	0.0007	−0.2588***	−0.2551***
	(0.0532)	(0.0006)	(0.0626)	(0.0730)
Female	−0.1840***	−0.0001	−0.2450***	−0.2709***
	(0.0338)	(0.0005)	(0.0458)	(0.0575)
Age group				
18–34	−0.1931**	0.0016*	−0.2910***	−0.2483**
	(0.0597)	(0.0006)	(0.0728)	(0.0854)
35–49	−0.1642**	0.0004	−0.2192***	−0.2086**
	(0.0473)	(0.0006)	(0.0599)	(0.0731)
50–64	−0.1813***	−0.0001	−0.2215***	−0.2270**
	(0.0437)	(0.0007)	(0.0591)	(0.0784)
≥65	−0.2408***	−0.0012	−0.3239***	−0.4151***
	(0.0488)	(0.0007)	(0.0691)	(0.0853)
Race/ethnicity				
White	−0.1926***	0.0001	−0.2523***	−0.2679***
	(0.0341)	(0.0005)	(0.0408)	(0.0506)
African American	−0.0953	−0.0023	−0.0601	0.0784
	(0.0897)	(0.0015)	(0.1359)	(0.1734)
Asian or Pacific Islander	0.3511**	0.0056***	0.2702	0.2796
	(0.1238)	(0.0014)	(0.1607)	(0.2259)
Other race or multi-race	−0.5704***	−0.0018	−0.6878**	−0.7283**
	(0.1596)	(0.0015)	(0.2101)	(0.2678)
Hispanic	−0.0753	0.0022	−0.2371	−0.2833
	(0.0745)	(0.0012)	(0.1253)	(0.1577)
Income group				
\$25,000 or less	−0.2519***	−0.0030**	−0.2347**	−0.1933*
	(0.0617)	(0.0010)	(0.0723)	(0.0845)
\$25,001–\$35,000	−0.0331	0.0002	−0.0188	0.1404
	(0.0567)	(0.0007)	(0.0660)	(0.0792)
\$35,001–\$50,000	−0.1682**	0.0001	−0.1992*	−0.2857**
	(0.0633)	(0.0011)	(0.0794)	(0.0909)
\$50,001 or more	−0.1836***	−0.0055***	−0.0446	−0.0231
	(0.0321)	(0.0005)	(0.0427)	(0.0564)

Note. (a) Individual data is from Behavioral Risk Factor Surveillance System 1990–2009 waves. (b) Monthly county unemployment rate is from US Department of Labor Bureau of Labor Statistics. (c) Income is based on annual county per capita income from the US Department of Commerce Bureau of Economic Analysis. It is converted to the 2009 US dollar using the all-items consumer price index from the US Bureau of Labor Statistics. (d) The treatment variable in all models is monthly county unemployment rate. (e) All models are OLS and control for individual characteristics (i.e., gender, age, race/ethnicity, education, and marital status) and county and year/month fixed effects. (f) Estimated standard error of coefficient is in parentheses. Eicker-Huber-White sandwich estimator is used to calculate standard error clustered at county level. (g) *$P < 0.05$, **$P < 0.01$, ***$P < 0.001$.

Although unemployment rate is a commonly used measure for labor market conditions, it does not capture discouraged workers and underemployment (e.g., mismatch between positions and specific skills). County unemployment rate is arguably a more relevant measure for local labor market fluctuations than is state unemployment rate, but measurement error can be negatively correlated with population size. In our analysis, this was unlikely to be an issue because most (93%) of the BRFSS sample came from large counties with a population above the median (respondents in very small counties were not identified), and a sensitivity test excluding small counties estimated nearly identical effects.

Ideally, nonlinear probability models such as Logit or Probit regressions should be used for models with the dichotomous variable denoting any physical activity as the dependent variable. However, it was computationally infeasible due to the inclusion of a large number (more than 2,600) of county fixed effects. We thus adopted a linear probability model instead. One major drawback of a linear probability model relative to a nonlinear one is that it violates the normality and homoskedasticity assumptions of the Ordinary Least Squares. In such case, the linear probability model compromises in estimation efficiency but the property of unbiaseness still holds. To account for heteroskedasticity,

Table 4: Estimated associations between past local labor market conditions and concurrent physical activity.

	Hours of physical activity per month	Any physical activity in the survey month	Hours of physical activity per month among existing exercisers (hours > 0)	Hours of physical activity per month among regular exercisers (hours ≥ 10)
1-month lag county unemployment rate	−0.1578***	−0.0012**	−0.1720***	−0.1668***
	(0.0271)	(0.0004)	(0.0347)	(0.0405)
2-month lag county unemployment rate	−0.0853**	−0.0004	−0.1098**	−0.1039**
	(0.0274)	(0.0004)	(0.0344)	(0.0394)
3-month lag county unemployment rate	−0.0230	0.0002	−0.0488	−0.0400
	(0.0276)	(0.0004)	(0.0343)	(0.0384)

Note. (a) Individual data is from Behavioral Risk Factor Surveillance System 1990–2009 waves. (b) Monthly county unemployment rate is from US Department of Labor Bureau of Labor Statistics. (c) The treatment variable in all models is lagged monthly county unemployment rate. (d) All models are OLS and control for individual characteristics (i.e., gender, age, race/ethnicity, education, and marital status) and county and year/month fixed effects. (e) Estimated standard error of coefficient is in parentheses. Eicker-Huber-White sandwich estimator is used to calculate standard error clustered at county level. (f) $*P < 0.05$, $**P < 0.01$, $***P < 0.001$.

we estimated standard errors clustered at county level using Eicker-Huber-White sandwich estimator. As a sensitivity analysis, we also weighted the linear probability model by the inverse of the multiplication between the estimated probability of doing any physical activity in the survey month and that of doing none. We obtained very similar quantitative results as when using the unweighted model with clustered standard error.

In spite of the many limitations which could compromise the evidence found in this study, there are a few important pathways that potentially link poor labor market conditions to reductions in physical activity, including financial stability, mental health status, and neighborhood environment, which all tend to deteriorate during major recessions. For example, neighborhood physical environment and safety play an important role in people's engagement in physical activity [17, 18]. The Great Recession resulted in an unprecedented surge in mortgage default and foreclosure [19], and vacant properties were found to contribute to neighborhood crime rate [20, 21], which may have discouraged physical activity among residents. To at least partially explore the influence of the Great Recession on physical activity, we reestimated the models in Table 2 based on the BRFSS 2002–2009 data. All four dependent variables in Table 2 (i.e., hours of physical activity per month, any physical activity in the survey month, hours of physical activity per month among existing exercisers, and hours of physical activity per month among regular exercisers) were found to be negatively correlated with county monthly unemployment rate.

Lack of physical activity and poor diet quality are the most pressing factors that contribute to the obesity epidemic in the US [22]. Using the BRFSS 1990–2009 waves, Dave and Kelly [23] found economic downturns to be associated with reduced consumption of fresh produce and increased consumption of fat foods such as snacks and fast food. In this study, we found evidence of the detrimental impact of labor market fluctuations on physical activity. The Great Recession has led to high unemployment rates that have stayed elevated even as other economic indicators have improved. The health consequences brought by this recession could thus be far reaching. The Gallup Healthways Wellbeing Survey conducted in mid-2011 showed that after more than two years, the Americans' physical activity was still below its 2008 level, and the largest decline was among individuals 65 years and older [24], which coincided with our findings on the high responsiveness of senior people's physical activity to economic downturns. Since this oldest age group is least attached to the labor market, financial and psychological stress due to job insecurity tend to be less relevant. Deteriorating neighborhood conditions could be a driven factor, but relevant evidence remains to be investigated.

No single study resolves a major research question. Establishing reliable empirical relationships (even without establishing causality) requires the accumulation of evidence through many studies. This correlational study has important design and measurement limitations, and future research with longitudinal or experimental study design is warranted. Nevertheless, our paper is among only a few to study the relationship between macroeconomic conditions and physical activity and adds a new data point with a focus on county-level unemployment. It suggests special attentions be paid to the potential detrimental impact on physical activity during major recessions.

References

[1] United States Department of Health and Human Services, "Physical activity guidelines for Americans," http://www.health.gov/paguidelines/guidelines/default.aspx, 2008.

[2] M. G. Marmot and R. Bell, "Action on health disparities in the united states commission on social determinants of health," *Journal of the American Medical Association*, vol. 301, no. 11, pp. 1169–1171, 2009.

[3] D. S. Ludwig and H. A. Pollack, "Obesity and the economy from crisis to opportunity," *Journal of the American Medical Association*, vol. 301, no. 5, pp. 533–535, 2009.

[4] B. Roshanaei-Moghaddam, W. J. Katon, and J. Russo, "The longitudinal effects of depression on physical activity," *General Hospital Psychiatry*, vol. 31, no. 4, pp. 306–315, 2009.

[5] J. E. Gómez, B. A. Johnson, M. Selva, and J. F. Sallis, "Violent crime and outdoor physical activity among inner-city youth," *Preventive Medicine*, vol. 39, no. 5, pp. 876–881, 2004.

[6] J. F. Sallis, H. R. Bowles, A. Bauman et al., "Neighborhood environments and physical activity among adults in 11 countries," *American Journal of Preventive Medicine*, vol. 36, no. 6, pp. 484–490, 2009.
[7] C. J. Ruhm, "Healthy living in hard times," *Journal of Health Economics*, vol. 24, no. 2, pp. 341–363, 2005.
[8] K. K. Charles and P. DeCicca, "Local labor market fluctuations and health: is there a connection and for whom?" *Journal of Health Economics*, vol. 27, no. 6, pp. 1532–1550, 2008.
[9] S. Nicholson and K. Simon, "How did the recession affect health and related activities of americans?" http://www.unc.edu/the/archives/simon.pdf, 2010.
[10] G. J. Colman and D. M. Dave, "Exercise, physical activity, and exertion over the business cycle," NBER Working Paper 17406, 2011, http://www.nber.org/papers/w17406.
[11] C. J. Ruhm and W. E. Black, "Does drinking really decrease in bad times?" *Journal of Health Economics*, vol. 21, no. 4, pp. 659–678, 2002.
[12] C. J. Ruhm, "Good times make you sick," *Journal of Health Economics*, vol. 22, no. 4, pp. 637–658, 2003.
[13] M. Bertrand, E. Duflo, and S. Mullainathan, "How much should we trust differences-in-differences estimates?" *Quarterly Journal of Economics*, vol. 119, no. 1, pp. 249–275, 2004.
[14] J. M. Wooldridge, "Asymptotic properties of weighted M-estimators for variable probability samples," *Econometrica*, vol. 67, no. 6, pp. 1385–1406, 1999.
[15] J. S. Butler, "Efficiency results of MLE and GMM estimation with sampling weights," *Journal of Econometrics*, vol. 96, no. 1, pp. 25–37, 2000.
[16] S. A. Prince, K. B. Adamo, M. E. Hamel, J. Hardt, S. Connor Gorber, and M. Tremblay, "A comparison of direct versus self-report measures for assessing physical activity in adults: a systematic review," *International Journal of Behavioral Nutrition and Physical Activity*, vol. 5, p. 55, 2008.
[17] United States Centers for Disease Control and Prevention, "Neighborhood safety and the prevalence of physical inactivity-selected states," *Morbidity and Mortality Weekly Report*, vol. 48, no. 7, pp. 143–146, 1999.
[18] R. C. Brownson, E. A. Baker, R. A. Housemann, L. K. Brennan, and S. J. Bacak, "Environmental and policy determinants of physical activity in the United States," *American Journal of Public Health*, vol. 91, no. 12, pp. 1995–2003, 2001.
[19] W. Brent, L. Kelly, D. Lindsey, and R. Price, "U.S. Mortgage foreclosures: an analysis by state," *Academy of Economics and Finance Journal*, vol. 1, pp. 17–30, 2010.
[20] L. Cui, "Foreclosure, vacancy and crime," Social Science Research Network Working Paper 1773706, 2011, http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1773706.
[21] I. G. Ellen, J. Lacoe, and C. A. Sharygin, "Do foreclosures cause crime?" http://furmancenter.org/files/publications/Ellen_Lacoe_Sharygin_ForeclosuresCrime_June27.pdf, 2011.
[22] United States Department of Agriculture and United States Department of Health and Human Services, *Dietary Guidelines For Americans*, United States Government, Washington, DC, USA, 7th edition, 2010.
[23] D. M. Dave and I. R. Kelly, "How does the business cycle affect eating habits?" *Social Science & Medicine*, vol. 74, no. 2, pp. 254–262, 2012.
[24] E. Mendes, "Americans still exercising less than before financial crisis," http://www.gallup.com/poll/148466/Americans-Exercising-Less-Financial-Crisis.aspx, 2011.