Who Is Hurt by Procyclical Mortality?

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Abstract

There is renewed interest in understanding how periodic fluctuations in mortality or health are related to fluctuations in economic conditions. The traditional perspective, that economic recessions are bad for health and mortality, has been challenged by new findings that suggest the reverse, at least in developed countries. The epidemiology of the phenomenon suggests that socioeconomically vulnerable populations may be disproportionately at risk during periods of heightened economic activity. Traffic accidents, stress-induced cardiovascular disease, and smoking and alcohol related illness appear to increase during period of rapid economic growth, and we know that socioeconomic status is normally correlated with the incidence of several of these diseases, and with poor health insurance coverage that might heighten risks. In this study, I examine mortality by individual characteristic and cause during the recessions and expansions of the 1980s using the U.S. National Longitudinal Mortality Study. I find that procyclical mortality is wide ranging in its impact, although there is evidence that vulnerable groups bear a disproportionately higher burden.

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1 Background and motivation

We typically assume that the downside of the business cycle is bad, and especially so for individuals of lesser means. The rise of the modern welfare state earlier in the past century and the development of social safety nets in industrialized countries were direct efforts to limit the pain inflicted by economic recessions. It is not surprising that the traditional perspective on the health impacts of economic fluctuations held that recessions were bad, especially for the most vulnerable members of society (Brenner, 1979). But a number of recent contributions have cast considerable doubt on this view, at least when applied to developed countries in the modern era. Ruhm (2000), Gerdtham and Ruhm (2002), Ruhm (2003), Laporte (2004), and Tapia Granados (2005) all explore empirical evidence that suggests precisely the opposite, namely that recessions are paradoxically good for health. As reviewed by Ruhm (2004), the recent literature is not completely of one voice on this topic. But much evidence currently suggests that procyclical mortality, or higher mortality during good macroeconomic times, is a significant pattern in the data worthy of further inquiry.

A key unanswered question is precisely who is vulnerable to procyclical mortality. Most of the previous studies in this area have decomposed the phenomenon by cause of death, which is easily done with national vital statistics.[1] Key findings are that external causes, in particular traffic accidents, appear to account for a large amount of procyclical mortality. The importance of cardiovascular disease is another common finding. Cirrhosis of the liver and other types of excesses-related mortality may also be part of the story. But an examination focusing solely of the causes of death is naturally limited and largely unsatisfactory for both researchers and policymakers hoping to improve public health. It is doubtful whether policies designed with this knowledge alone could effectively ameliorate procyclical mortality without depressing economic activity, or essentially throwing the baby out with the bathwater (Edwards, 2005).

Who are the victims of procyclical mortality? Are they spread evenly across socioeconomic classes, or are they concentrated in a particular range? Information on causes of death does not offer a concise story here. Traffic fatalities could be suburban commuters or inner-city pedestrians. Heart attack victims could be the hard-living working poor, high-stress executives, or some combination. Edwards (2005) discusses how in the U.S., health in-

[1] Granted, those studies based on time-series data typically use data recorded far in the past. Problems associated with changing cause classification and autopsy prevalence over such long spans of time are well known and must be addressed in such studies.

surance coverage is in one sense countercyclical, rising during recessions and falling during expansions. Medicaid, the public medical insurance program for Americans under age 65, is means-tested, so it is naturally countercyclical. We know that a large portion of those without medical insurance in the U.S. are the working poor (Glied, 2001). Given these facts, a key question is to what extent these working poor may be especially vulnerable during periods of rapid economic growth in the U.S.

The unique design of the National Longitudinal Mortality Study (NLMS) makes it a valuable tool for seeking answers to these questions. Over half a million individuals sampled in several Current Population Surveys around 1980 were matched to death records during the subsequent nine years to form the NLMS. The dataset therefore measures mortality and the standard CPS covariates, such as education, occupation, and income, at the individual level for a large number of people over nine years of time in the 1980s. The 1980s were a macroeconomically interesting period in the U.S., with two recessions, one short expansion, and one very long expansion. According to the Business Cycle Dating Committee of the National Bureau of Economic Research, macroeconomic activity peaked in January 1980 and declined until July of that year. The subsequent recovery lasted only a year, stalling in July 1981. After November 1982, the American economy entered the second longest peacetime expansion in its history, which ended in July of 1990. According to official statistics, the civilian unemployment rate hit a peak of 9.7 percent in 1982, almost 3 percentage points about its 1980 level, and then began to decline, ultimately reaching 5.3 percent in 1989. Annual growth in GDP was as low as -1.9 percent in 1982, as high as 7.2 percent in 1984, and it averaged about 4 percent after 1985.

In the sections that follow, I examine procyclical mortality using the public file of the NLMS. Section 2 begins by describing the dataset in greater detail. In Section 3, I run a diagnostic check of the NLMS by exploring whether aggregated NLMS mortality data exhibits procyclical fluctuations similar to those that other researchers have found in aggregate data. Next, I descend to the individual level in the NLMS and model annual death probabilities as functions of individual characteristics and contemporaneous macroeconomic conditions in Section 4. Section 5 offers concluding remarks.

2 The National Longitudinal Mortality Study

The U.S. National Longitudinal Mortality Study (NLMS), maintained by the the National Heart, Lung, and Blood Institute (NHLBI) of the U.S.

Census, is a panel dataset of individuals interviewed in Current Population Surveys (CPS) and then subsequently matched to death certificates via the National Death Index. The NDI match identifies time of death down to six-hour groupings, along with cause of death and several other death certificate data, which is linked to individual socioeconomic characteristics through the CPS data. The NLMS is the only large-scale dataset capable of linking U.S. deaths to detailed characteristics. Panel data like the Health and Retirement Study measure mortality, both through proxy interviews and NDI matching, but smaller sample sizes produces much noise in age-specific mortality rates.

The NLMS data exist in two forms: the restricted database, which covers many CPS cohorts and many years of follow-up; and the smaller public file. The current version of the public file follows 637,162 individuals over 3,288 days, or roughly 9 years. In order to improve confidentiality in the public file, the NHLBI has intermingled CPS cohorts without identifying them, leaving precise calendar dates unclear. We know from Preston and Elo (1995) that the public file contains individuals from five different CPS cohorts sampled between March 1979 and March 1981. The midpoint of this period is March 1980, which I specify as the approximate beginning of the entire panel in the public file. Under this assumption, assumed dates may be wrong by a full calendar year in either direction, which is certainly a large amount of potential error. Thus we would expect mortality data drawn from the public file to be like a three-year moving average of the true data, which may hamper investigation of cyclical trends.

The structure of the NLMS dataset facilitates the analysis of mortality at the individual level, to which we will ultimately turn. It is useful to begin by examining aggregate mortality statistics in the NLMS relative to official mortality statistics, and also relative to indicators of the business cycle like GDP and employment. We are interested in whether these time-averaged NLMS data look at all like official annual statistics, and by extension whether they exhibit the same relationship to macroecononomic variables found by earlier researchers studying national and state-level aggregate data.

3 Aggregated NLMS data

3.1 Levels, trends, and volatility in mortality

A natural first question to ask is whether annual NLMS mortality data look like national vital statistics. Figure 1 plots age-adjusted mortality rates for individuals of both sexes at age 10 and over in the NLMS and in data from the Human Mortality Database (2006), drawn from national vital statistics. I stop both series after 1988 because I find that 1989 NLMS data, which reflects only about the first 75 days of the year, is noisy. Here and in the rest of the paper, I drop observations from the last 75 days of the NLMS public file.[2]

It is clear that the aggregated NLMS mortality series differs from official data in level, in trend, and in volatility around the trend. As remarked by Preston and Elo (1995), the NLMS yields mortality rates that are lower than national vital statistics because it undersamples higher institutionalized mortality. The CPS covers noninstitutionalized populations only; while some CPS respondents may later enter an institution and die, which the NLMS would measure, the NLMS does not measure institutionalized mortality at least at the start of the sample period.

This fact may also explain why there is basically no time trend in aggregated NLMS mortality, while vital statistics clearly show the downward trend we expect to see. Since some CPS respondents surely entered nursing homes and died, they probably only died later during the sample period. Those individuals with higher mortality rates would be basically not represented at all during the beginning of the sample and then at least partially represented toward the end, biasing the time trend in mortality upward.

Annual variation in NLMS mortality around its trend looks rather different than its counterpart in official statistics. The upward spike in 1984 in the lower NLMS series is not at all present in the official series above it, for example. But as mentioned before, we also know that 1984 was a period of rapid economic growth, with the highest annual growth rate in real GDP during the decade at 7.2 percent.

3.2 Procyclical mortality

The logical next step is to ask whether aggregate NLMS mortality and macroeconomic activity display the same relationship that other researchers have discovered between vital statistics and GDP, unemployment, hours worked, or other macroeconomic variable. We posit that macroeconomic activity, such as measured by GDP, raises mortality m_{it} for individual i at time t aged x_{it}:

$$\log m_{it} = \alpha_i + \delta(x_{it}) \cdot t + \gamma \cdot \log GDP_t + \beta x_{it} + \vec{B} \cdot \vec{X}_{it} + \epsilon_{it}, \qquad (1)$$

[2]There are 75 days from the beginning of the year to March 15, 1989, which is 9 years after March 15, 1980.

where α_i is an individual fixed effect, $\delta(x_{it}) < 0$ is the age-specific rate of decline, $\vec{X}_{it}$ is a vector of characteristics other than age x_{it}, and ϵ_{it} is a white-noise error. In annual aggregate data, it is convenient to assume that the characteristics of the representative individual remain fixed over time and proceed to difference equation (1), which leaves us with

$$\Delta \log \bar{m}_t = \bar{\delta} + \gamma \Delta \log GDP_t + \epsilon_t, \tag{2}$$

where bars over variables denote age-adjusted averages.

Figure 2 plots changes in log mortality from the NLMS and HMD along the vertical axis against changes in log real GDP from the Bureau of Economic Analysis, with trendlines from ordinary least squares estimates of equation (2) superimposed. The NLMS data, shown with triangles, are certainly more volatile than the HMD data, shown with circles. The upshot of this volatility is a strengthening of the simple bivariate relationship between mortality and GDP, as evidenced by the slopes of the trendlines, which are the γ in equation (2). To be sure, statistical significance is not high with only 8 data points. In the NLMS data, γ is estimated at 0.68 with a standard error of 0.40; in the HMD data, it is estimated at 0.27 with a standard error of 0.16.

Still, these findings bode well for an examination of NLMS mortality at the individual level. Since we see procyclical mortality using aggregate NLMS data, chances are good that individual-level NLMS data will yield interesting results. We next turn to modeling the mortality of individuals in the NLMS.

4 NLMS death probabilities, individual characteristics, and the macroeconomy

With data on individual deaths, we have several choices of statistical modeling techniques.[3] A good fit for data on deaths by age is the logit model, since the logit transformation of mortality rates is highly linear in age (Himes,

[3] One approach is to exploit the duration data contained in the NLMS with a Cox proportional hazards or similar model. The NLMS reports the number of days between entrance and exit, either through mortality or right-censoring. Modeling the relationship between mortality and external conditions at daily, weekly, monthly, or quarterly frequencies is a promising avenue for research, but for now I leave it for future pursuits. The public file of the NLMS does not tell us the exact calendar date of death, and there is roughly a year of time of potential error around the date, so moving from annual to higher-frequency analysis seems unwise.

Preston and Condran, 1994). I therefore modify equation (1) by placing the logit transformation of individual i's death probability q_{it} on the left-hand side:

$$\log\left(\frac{q_{it}}{1-q_{it}}\right) = \alpha + \delta \cdot t + \gamma \cdot \Delta \log GDP_t + \beta x_{it} + \vec{B} \cdot \vec{X}_{it} + \epsilon_{it} \tag{3}$$

Rather than use the *level* of macroeconomic activity as a covariate for the level of the logit of mortality, I instead include the *chanrge* in activity relative to last year. Theory suggests it is deviation from trend growth that produces procyclical mortality, and while the NLMS mortality series exhibits stationarity (Figure 1), GDP does not. Also, I drop individual fixed effects and age specificity of the time trend for now for computational simplicity.

I estimate the logit specification in (3) using pooled annual NLMS data on exposures and deaths. To produce the latter, I first split the NLMS data into annual observations on deaths and exposures that I match to calendar years, with the same known problem of error in the dating of the public-file records. Each year's observations contains only those individuals still alive at its beginning. Then I update individuals' ages appropriately and match observations with macroeconomic data in those years. Finally I pool observations across years and run a single regression model with all years represented.

4.1 Full results by age for men and women

Tables 1 and 2 display complete regression results from modeling (3) on pooled NLMS data for females and then for males in the three age groups specified along the columns, 25–64, 65–79, and 80 and over. I include the same set of covariates used by Elo and Preston (1996) in their study of educational disparities in the NLMS data. In each table, I include the standard error of the estimate of γ, the coefficient on the change in log GDP per capita, to facilitate easier comparison across point estimates. For brevity, I omit standard errors of other coefficients.

Estimates of the Elo-Preston covariates and their significance levels are virtually identical to earlier results. One exception is that there is a significant positive time trend in female mortality above age 65 between 1980 and 1988 in the NLMS data, shown in the first row of Table 1. This is not present in official statistics and probably reflects the lack of institutionalized individuals earlier in the sample, an effect that is magnified for females, who are more likely to become institutionalized at advanced age. Table 2 shows no time trend among males, which is consistent with the aggregate data shown earlier in Figure 1.

Other covariates are associated with mortality in the standard way. An additional year of age raises the odds of dying at a steady rate of about 8.5 percent for females; among males, there is some heterogeneity around a similar figure. Being African-American raises the log odds of dying for most younger age groups, but there are signs of lower mortality among African Americans at advanced ages.[4] Being born outside of the Northeast is associated with lower odds of dying across the board. Education, income, being married, and living in a rural area are all protective.

The fourth and fifth rows from the bottom in each table depict the coefficients on the change in log GDP per capita and their standard errors. Point estimates range between 1 and 2.5 for females, and 1.8 and 2.3 for males. A coefficient of 2 associates a 1 percent rise in $\Delta \log GDP$ per capita with a 2 percent rise in the odds ratio. This is high in comparison to previous findings in the literature (Tapia Granados, 2005), which tend to report coefficients that are around 10 times smaller, in the neighborhood of the slope of 0.27 shown in Figure 2 in official statistics.[5] We have already seen that aggregated NLMS data produce a larger correlation between changes in log mortality and log GDP during this period, but only 2–3 times as large.

As a check, I also ran the model with either the change in the unemployment rate or the change in the employment to population ratio in place of the change in log GDP per capita. From those two regressions, I recovered coefficients and standard errors of -0.030 (0.006) on the unemployment rate or 0.046 (0.010) on the employment per population (not shown), both of which were significant at the 1 percent level. These coefficients are more consistent with other results in the literature (Ruhm, 2000; Gerdtham and Ruhm, 2002; Tapia Granados, 2005). Why the coefficient on $\Delta \log GDP$ per capita is so much higher than in other findings remains unclear. If anything, the 1980s were a time of relatively more volatile growth in GDP overall and relative to change in unemployment than in other time periods, which we would expect to result in a smaller coefficient on GDP given the coefficient on unemployment.

Unlike the unemployment rate, GDP per capita captures the intensive margin of economic activity, the effort or productivity per unit of input, as

[4] Whether this is a real mortality crossover, where blacks have lower mortality than whites at old ages, remains unclear. All we know currently is that it is a difference in the age-slope of mortality.

[5] The difference in results cannot be due to the discrepancy between log odds and log mortality. For small mortality rates and small changes in them, the percentage change in the oddds ratio is roughly equal to the percentage change in the mortality rate, although the former is greater than the latter. Formally, $\log(q/[1-q]) \approx \log q + q > \log q$.

well as the extensive margin, or the proportion of inputs that are active. If both margins are important for average health, as seems likely to be the case, then GDP per capita is the preferred measure. Since results are qualitatively similar across measures of macroecononic conditions, I report results using $\Delta \log GDP$ per capita in the rest of the paper.

We do not see large differences across age and sex groups in the coefficient on $\Delta \log GDP$ per capita in Tables 1 and 2. Point estimates decline somewhat with age, but the differences are not statistically significant. There is no statistically significant effect of macroeconomic conditions on the mortality of women aged 65–79, although there is for women over 80. By comparison, Tapia Granados (2005) reports gradually decreasing effects through age that then increase at advanced ages.

4.2 Differential results by race, SES, and occupation

A key advantage of the NLMS is that by virtue of its development from CPS files, it measures many more individual characteristics than are in the standard set available on death certificates. Using NLMS data, I can test for differential impacts of procyclical mortality by individual or group characteristics in two ways. I can insert interaction effects into the regressions in Tables 1 and 2 and test their significance, or I can run separate models by subgroup and compare results across them. The former forces noninteracted coefficients to be the same across all individuals, while the latter does not.

In Table 3, I reestimate the models in the two earlier tables with four new interaction terms based on $\Delta \log GDP$ and race, income, and education dummy variables. I report only a subset of parameter estimates along with their standard errors. For females, depicted in the top panel, the significance of individual coefficients largely evaporates with the addition of interaction terms, and the emerging story is not very clear. For women of working age, all interaction terms end up positive, even the one that interacts being in the top 30 percent of family incomes with macroeconomic conditions. Many of these terms switch sign back and forth through age. For men, the story is a little better. Being African-American always enlarges the impact of macroeconomic conditions, although not always significantly, while being in the top 30 percent of family incomes reduces it. Being in the bottom 10 percent of income actually reduces procyclical mortality for males aged 25–64, at least for those who are not African-American. There is no clear interaction between having attained a high school diploma and macroeconomic conditions.

The picture becomes clearer when I run separate regressions on subgroups and compare coefficient estimates across models. Table 4 displays key results for subgroups identified by race, sex, and age. Differences between African Americans and others are clearest in the top four rows, which do not separate age groups. For males who are white or of other racial background, hereafter referred to as white, the coefficient on $\Delta \log GDP$ per capita is 1.6, and it is similar for females of the same races. The story is similar for female African Americans, although both the coefficient and its standard error have increased. At about 4.0, the coefficient for African-American men is more than twice as large as that for whites. To be sure, confidence intervals around these point estimates are large, but how much they vary is still noteworthy.

The next three sets of rows break down the race/sex subgroups by age. Coefficients do not change with age for white males, but they fluctuate quite a bit with age for other groups. We see the same pattern as before for white females, namely strong effects of the macroeconomy during working ages, weak effects at ages 65–79, and strong effects again after age 80. African-American males experience a similar gradient through age, but at a higher level, while African-American females experience a monotonic decline through age, also from a high level.

In Table 5, I explore how procyclical mortality differentially affects income, educational, and geographic groups using separate logit models for each. The top two rows suggest that procyclical mortality is not about being poor. The coefficient on $\Delta \log GDP$ per capita is actually lower for those in the lowest income decile as compared to the rest of the population, although the difference is not statistically significant. In fact, this story changes slightly when we differentiate by sex as well as income in rows 3 through 6. Males in the lowest decile, earning below $10,000 a year in 1980, have a higher coefficient than males in the upper 90 percent, while for females the pattern is reversed. We might imagine that differential working behavior, something we will explore in Table 6, could be responsible for these patterns. Whether cause or effect, females in low-income families probably do not work, while females in high-income families probably do. Males probably work regardless of income, so the differences between high and low-income males here speaks to the impacts of something else, perhaps occupation or health insurance coverage. We can examine the former but not the latter in these data, which we turn to in Table 6. Interestingly, females in the upper 90 percentile are most at risk from procyclical mortality among these subgroups.

Although low-income groups do not appear to be disproportionately at risk from procyclical mortality, do high-income groups also suffer from procyclical mortality? The next set of rows, which examines the split between the bottom 70 percent and top 30 percent of income, shows that high income seems to be protective against procyclical mortality. Those in the top 30 percent, earning more than \$50,000 per year in 1980 or the equivalent of about \$120,550 today, basically felt no procyclical mortality, while those in the first 70 percent experienced roughly the average effect. Breakdowns by sex follow roughly the same pattern as with the 10-90 split, but it is unclear whether high-income females really experience procyclical mortality that is twice as strong as the other groups or whether the small sample size is the culprit.

The next rows in Table 5 explore differential impacts by education. The split at high school attainment yields some interesting patterns, basically reaffirming earlier findings on income, but differences are less stark. Males with lower education are somewhat more subject to procyclical mortality, while females with lower education actually are subject to less. Finally, the last two rows in the table depict similar trends along the urban/rural split. Those who live in rural areas and who probably have lower socioeconomic status have a coefficient of about 2.1, while those who live in urban places register 1.6.

The differences we see in impacts by sex certainly suggest that labor force participation may be an important element of the story, and Table 6 explores this. The first row shows that individuals who in the labor force, employed, and who worked during the week of the initial CPS interview were also subject to much procyclical mortality, with a coefficient on $\Delta \log GDP$ per capita around 2.4. Interestingly, those people who reported themselves employed but not working in the interview week, listed in the second row, were not exposed to any discernible procyclical effect at all. According to the BLS, such individuals are either on vacation, ill, experiencing child-care problems, taking care of family or personal obligations, on maternity or paternity leave, involved in an industrial dispute, or prevented from worked by bad weather. Individuals who report not working in this way must have jobs with some flexibility, a characteristic that is tempting to associate with lessened exposure to procyclical mortality. Those who are unemployed and looking for work do not experience statistically significant procyclical mortality because the standard error is so high, even though the point estimate is the largest of the four in this top panel. Still, working and how we work are not the whole story; those not in the labor force at all are still subject to procyclical risks, a pattern that is consistent with earlier results by age group.

In the lower panel of Table 6, I explore procyclical mortality by occupational group among everyone in the NLMS who answered the question, current and retired workers combined. The top four groups — professional and technical workers, nonfarm managers and administrators, sales workers, and clerical workers — were originally designated "white collar," while the next four were "blue collar," followed by two farming categories and finally two categories of service workers. The BLS changed its occupational categories in 1983, citing a wish to remove the pejorative, and increasingly socioeconomically meaningless, label of "blue collar" (Bregger, 1982).

The group with the highest sensitivity to macroeconomic conditions consists of transport operatives, with a coefficient of 6.1. This group includes bus and truck drivers, along with operators of boats and trains. That procyclical mortality would be especially high for bus and truck drivers is consistent with findings elsewhere that mortality due to traffic accidents is high during economic expansions. But the group with the second highest coefficient is that of nonfarm managers and administrators, which is comprised of bank officers, public administrators, postmasters, school administrators, and so on. That individuals in positions of authority who supervise others suffer from relatively more procyclical mortality fits with our understanding of the epidemiology of it. During periods of heady growth, middle management is probably under the most job stress, asked by forces above to increase productivity and constrained by the behavior of forces below. We know that stress-related illnesses like coronary heart disease and hypertension rise during good times, and they probably afflict these managers. There is considerable heterogeneity among the other occupations. Professional and technical workers, nonfarm laborers, and farmers and farm managers have negative coefficients, while other occupations have positive coefficients, all with varying degrees of statistical significance.

4.3 Results by underlying cause of death

The NLMS codes deaths according to underlying cause of death as reported on the death certificate. I combine causes classified using the ICD-9 system into a superset of eight using the categories specified by Vaupel and Romo (2003) and the Berkeley Mortality Database (2006). Total deaths in the pooled NLMS dataset attributable to each of these eight causes are listed along with exposures in Table 7. A small share of deaths, 0.3 percent, are not categorized by underlying cause, and a very small share, less than 0.1 percent, are attributable to senility without psychosis. Heart and hypertensive disease accounted for over a third of all deaths and cancer one quarter. Violent deaths such as accidents and homicides accounted for only

6.4 percent.

Table 8 shows that deaths due to all eight of these cause supersets are more likely during economic good times; all regression coefficients are positive. Compared to all deaths, which is the left-hand-side variable in the bottom row of the table, heart and hypertensive causes in the first row appear to be less sensitive than the average cause of death to the business cycle in NLMS data, which is somewhat unexpected. As usual, however, the two coefficients have overlapping confidence intervals. The coefficient in the cancer deaths regression is virtually the same as the all-cause coefficient, and the rest of the causes exhibit greater than average procyclicality. With the exception of cancer deaths, which are procyclical here, these results have the same sign as those of Tapia Granados (2005), who also separated suicides from violent deaths in aggrgate data and reported the former to be counter-cyclical. A difference is that I find cardiovascular disease to be less strongly procyclical than other diseases, while he discovered the opposite.

5 Discussion

There are many unanswered questions regarding the levels of health and mortality and what produces them. This paper takes a different approach in focusing on the dynamics of mortality over time. Although much productive research focuses on long-term trends in mortality, here we examine short-term volatility in mortality, guided by recent and provocative findings in the burgeoning mini-industry that studies how mortality fluctuates over the economic business cycle.

Researchers have previously used the National Longitudinal Mortality Study to inform knowledge of the levels of health and mortality at a point in time, and it is an unparalleled resource for helping disaggregate mortality by individual characteristic. This paper has shown that despite acknowledged shortcomings, the public file of the NLMS is also a powerful tool for understanding short-term temporal patterns in mortality, even if the secular trends we know must exist remain obscured. Surely the coverage of institutional mortality must be an important issue here, and a more careful treatment of it awaits future efforts.

Consistent with other recent papers, I have shown here that the incidence of procyclical mortality in the U.S. is fairly wide-ranging. It is not easy to identify subgroups that are particularly at risk from higher mortality during business cycle expansions; procyclical mortality is a broad-based risk that evidence suggests is a fact of modern life in an industrialized society. With that said, we can still identify groups that are more or less at risk, which leads us toward better understanding the phenomenon and better policy advice. And there remain significant gaps in our knowledge owing to the inevitable constraints of data.

One clear finding is that African Americans, especially young males, are at relatively greater risk of procyclical mortality. Two potential explanations for this phenomenon come to find. We know from other results in this paper that cardiovascular disease is procyclical, and we also know that African Americans are typically face heightened risks of developing cardiovascular disease, for either genetic, environmental, or behavioral reasons. It may also be the case that African Americans disproportionately engage in occupations that place them at greater risk during periods of heightened economic activity, such as operating transportation equipment.

Another pattern that emerges from these data is that while being poor does not much heighten the risk of procyclical mortality, although it may raise it somewhat for men, being rich seems to dampen its effects considerably, at least for men. The finding that poverty does not heighten risk is somewhat counter-intuitive. To be sure, Medicaid, which is means-tested, has historically covered between 10 and 15 percent of the population. So the bottom decile of the income distribution may have at least some basic level of health insurance. But many of these individuals are working poor, and presumably they would be subject to similar if not identical job-related stresses stemming from heightened economic activity.

Part of the story seems to involve female labor force participation. We do see higher procyclical mortality among poor men as opposed to the average, and we see less among poor women, who are probably not working. The story reverses at the top of the income distribution, where rich men are insulated from procyclical mortality, if anything suffering higher mortality during periods of idleness, while rich females may actually have higher procyclical mortality than average.

When we look at labor supply, we definitely see that those who are working are subject to higher risks during good times. We also see that those out of the labor force are subject to procyclical risks of death, and we find an interesting pattern among employed workers who were not working during the week of CPS interview. This last group, which demonstrably enjoys flexible working arrangements, does not seem to suffer cyclical mortality at all. Workers in this group presumably have more control over when they want to work and how hard, and without surprise, that seems to matter for procyclical mortality.

Evidence on differential risk by occupation mirrors this lesson and another. Aside from tranportation operatives, it is middle management that appears to suffer the most from procyclical mortality. These are probably the people who do not have the job control enjoyed by the CEOs who issue them orders or by the professional/technical workers in academia, in the health industry, and elsewhere. They also probably do not enjoy union protections such as limits on and rewards for overtime which laborers may appreciate. But as vulnerable to procyclical mortality as managers may be, at least they do not drive trucks. Patterns by cause of death certainly affirm that traffic accidents and other violent deaths are procyclical, but results are relatively homogeneous across causes. Where they are not is somewhat unexpected given earlier findings: cardiovascular disease in the NLMS is procyclical, but not as strongly so as other causes.

The picture we have painted with this new evidence is thus mixed but informative. We know a fair amount about how working and procyclical mortality go together based on the NLMS. This comes as no big surprise given that the NLMS originated with the Current Population Survey, which focuses on the supply side of the labor market. A key direction for future research, along with the refinement of results presented here, is a closer examination of procyclical mortality at older ages, when the macroeconomy channeled through the work environment clearly cannot be a proximate determinant of health outcomes.

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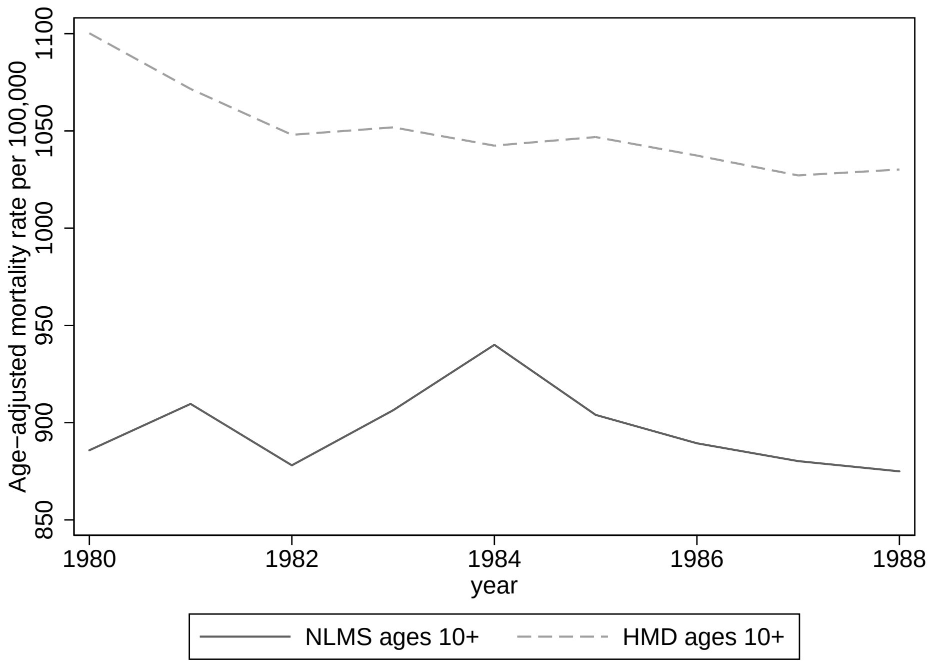
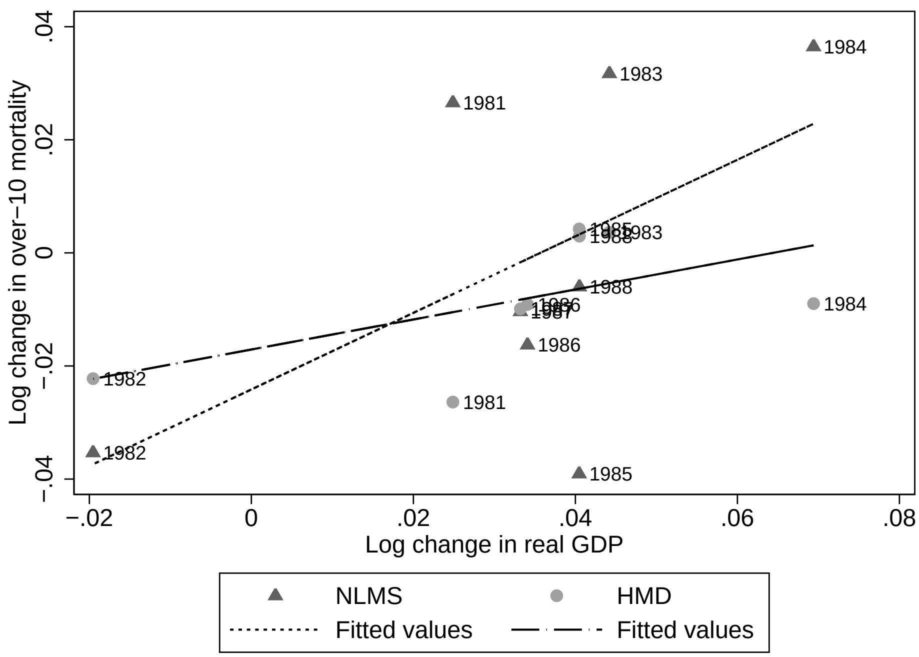
Figure 1: Age-adjusted mortality rates for both sexes combined, 1980–1989



Notes: This figure shows age-adjusted mortality rates for both sexes combined at ages 10 and over. Data are drawn from the Human Mortality Database (2006) and the National Longitudinal Mortality Study (NLMS). Age-adjusted rates are constructed using age-specific mortality rates and the age distribution in 1990 as provided by the HMD.

Figure 2: Changes in log mortality versus changes in log real GDP 1980–1988



Notes: This figure plots changes in log age-adjusted mortality rates for both sexes combined at ages 10 and over from two different sources — the National Longitudinal Mortality Study (NLMS), shown in triangles, and the Human Mortality Database (2006), shown in circles — against changes in log real GDP provided by the U.S. Bureau of Economic Analysis. Age-adjusted rates are constructed using age-specific mortality rates and the age distribution in 1990 as provided by the HMD. Trendlines are ordinary least squares fits of the each data series to a constant plus GDP growth. In the NLMS data, the slope is estimated at 0.68 with a standard error of 0.40; in the HMD data, it is estimated at 0.27 with a standard error of 0.16.

Table 1: Logit regressions of females' annual log odds of dying in the NLMS on individual level characteristics and changes in macroeconomic conditions

		FEMALES	
Variable	**Ages 25-64**	**Ages 65-79**	**Ages 80+**
Time	0.007	0.032***	0.022***
Age	0.086***	0.084***	0.087***
African American	0.240***	0.111**	−0.145**
Other race	0.239**	−0.152	−0.424***
Born: South	−0.022	−0.046	−0.014
Borth: Midwest	−0.019	−0.052	−0.101**
Born: West	−0.087	−0.046	−0.100
Born: Elsewhere	−0.427***	−0.345***	−0.109**
0-7 years of school	0.266***	0.129***	0.032
8 years of school	0.259***	0.061	0.100**
9-11 years of school	0.198***	0.083**	0.039
13-15 years of school	−0.002	−0.164***	−0.022
16 years of school	−0.236***	−0.136**	0.050
Log family income in 1980	−0.387***	−0.128***	−0.011
Household size	−0.030**	0.036**	0.048***
Widowed	0.126**	0.153***	0.050
Divorced	0.121**	0.241***	0.167*
Never married	0.195***	0.099	0.078
Live in central city (CC)	0.179***	0.101***	−0.000
Live in metro area, non-CC	0.138***	0.069**	0.041
$\Delta \log GDP$ per capita	2.279***	0.995	2.485***
(standard error)	(0.821)	(0.651)	(0.693)
Constant	−9.662***	−9.981***	−10.198***
N	1,148,971	236,074	73,924
χ^2-stat	3,768	1,023	961

Notes: Asterisks denote statistical significance at the 1% (three), 5% (two) and 10% (one) level. Each column shows the coefficient estimates from a logit regression of the log odds of dying during a calendar year between 1980 and 1988. The year-to-year change in log real GDP per capita from 1980–1988 is obtained from the U.S. Bureau of Economic Analysis. All other data are from the National Longitudinal Mortality Study (NLMS). Observations are individuals observed alive and either surviving or dying during each year between 1980 and 1988, where annual observations are pooled. The time variable starts at 0 and indexes years. The default category is a white individual born in the Northeast with 12 years of education, who is married and not living in a metro area.

Table 2: Logit regressions of males' annual log odds of dying in the NLMS on individual level characteristics and changes in macroeconomic conditions

	MALES		
Variable	**Ages 25-64**	**Ages 65-79**	**Ages 80+**
Time	−0.006	−0.003	0.002
Age	0.087***	0.071***	0.058***
African American	0.233***	−0.085*	−0.249***
Other race	0.196**	−0.309***	−0.249*
Born: South	0.000	0.020	−0.024
Borth: Midwest	−0.058	−0.035	0.071
Born: West	−0.141***	−0.188***	−0.074
Born: Elsewhere	−0.558***	−0.343***	−0.156***
0-7 years of school	0.082	0.081**	−0.053
8 years of school	0.178***	0.117***	0.011
9-11 years of school	0.137***	0.104***	−0.018
13-15 years of school	−0.022	−0.050	0.009
16 years of school	−0.309***	−0.221***	−0.104
Log family income in 1980	−0.490***	−0.254***	−0.121***
Household size	−0.008	0.051***	0.011
Widowed	0.402***	0.200***	−0.015
Divorced	0.352***	0.300***	0.162*
Never married	0.400***	0.115**	0.024
Live in central city (CC)	0.129***	0.117***	0.124***
Live in metro area, non-CC	0.037	0.031	0.050
$\Delta \log GDP$ per capita	2.247***	1.760***	1.889**
(standard error)	(0.643)	(0.557)	(0.788)
Constant	−8.844***	−8.181***	−7.001***
N	1,045,344	179,721	37,865
χ^2-stat	6,032	1,265	302

Notes: Asterisks denote statistical significance at the 1% (three), 5% (two) and 10% (one) level. Each column shows the coefficient estimates from a logit regression of the log odds of dying during a calendar year between 1980 and 1988. The year-to-year change in log real GDP per capita from 1980–1988 is obtained from the U.S. Bureau of Economic Analysis. All other data are from the National Longitudinal Mortality Study (NLMS). Observations are individuals observed alive and either surviving or dying during each year between 1980 and 1988, where annual observations are pooled. The time variable starts at 0 and indexes years. The default category is a white individual born in the Northeast with 12 years of education, who is married and not living in a metro area.

Table 3: Logit regressions of annual log odds of dying in the NLMS on individual level characteristics, changes in macroeconomic conditions, and interaction terms: partial results

	FEMALES		
Variable	**Ages 25-64**	**Ages 65-79**	**Ages 80+**
$\Delta \log GDP$ per capita	0.287	2.004*	2.289*
	(1.470)	(1.189)	(1.237)
African American × $\Delta \log GDP$ per capita	2.006	1.412	−3.417
	(1.999)	(1.847)	(2.352)
Top 30% of family income × $\Delta \log GDP$ per capita	3.910	−0.696	0.025
	(3.049)	(3.845)	(3.983)
Bottom 10% of family income × $\Delta \log GDP$ per capita	1.460	−0.710	0.618
	(1.449)	(1.108)	(1.213)
High school grad × $\Delta \log GDP$ per capita	1.678	−1.648	0.005
	(1.508)	(1.176)	(1.335)
N	1,148,971	236,074	73,924
χ^2-stat	3,773	1,026	964

	MALES		
Variable	**Ages 25-64**	**Ages 65-79**	**Ages 80+**
$\Delta \log GDP$ per capita	3.036***	1.353	−0.674
	(1.077)	(0.921)	(1.360)
African American × $\Delta \log GDP$ per capita	3.121*	1.407	1.237
	(1.638)	(1.658)	(2.741)
Top 30% of family income × $\Delta \log GDP$ per capita	−2.418	−6.874**	−2.757
	(2.419)	(2.935)	(4.488)
Bottom 10% of family income × $\Delta \log GDP$ per capita	−2.456**	0.849	3.320**
	(1.187)	(0.928)	(1.341)
High school grad × $\Delta \log GDP$ per capita	−0.723	−0.206	1.017
	(1.156)	(1.029)	(1.561)
N	1,045,344	179,721	37,865
χ^2-stat	6,040	1,273	309

Notes: Asterisks denote statistical significance at the 1% (three), 5% (two) and 10% (one) level. Each column shows selected coefficient estimates and standard errors from a logit regression of the log odds of dying during a calendar year between 1980 and 1988, with the full set of covariates listed in Tables 1–2 (not shown), including a constant and a time trend, plus the interaction terms listed here. See the notes to Tables 1–2 for further details.

Table 4: Coefficients on $\Delta \log GDP$ per capita in logit regressions restricted to age/race/sex subgroups: partial results

Subgroup	**Coef. on $\Delta \log GDP$**	**Standard error**	**N**	**χ^2-stat**
White/other males	1.604***	(0.388)	1,363,119	32,468
White/other females	1.707***	(0.433)	1,520,127	30,116
African-American males	4.039***	(1.144)	131,416	3,000
African-American females	2.038	(1.242)	176,975	2,921
White/other males 80+	1.617**	(0.818)	34,806	284
White/other females 80+	2.646***	(0.720)	68,524	942
African-American males 80+	5.264*	(2.944)	3,059	29
African-American females 80+	0.451	(2.569)	5,400	43
White/other males 65-79	1.698***	(0.584)	165,947	1,159
White/other females 65-79	0.907	(0.688)	215,943	939
African-American males 65-79	2.442	(1.846)	13,774	98
African-American females 65-79	1.795	(2.003)	20,131	68
White/other males 25-64	1.696**	(0.693)	958,233	5,031
White/other females 25-64	1.951**	(0.896)	1,028,524	3,127
African-American males 25-64	5.651***	(1.719)	87,111	836
African-American females 25-64	4.042**	(2.063)	120,447	576

Notes: Asterisks denote statistical significance at the 1% (three), 5% (two) and 10% (one) level. Each row shows the estimated coefficient on $\Delta \log GDP$ per capita, its standard error, the number of observations, and the χ^2 statistic from a logit regression of the log odds of dying during a calendar year between 1980 and 1988, with a full set of covariates listed in Tables 1–2 (not shown), including a constant and a time trend, less the dummy variables specific to the group for which the regression is run. See the notes to Tables 1–2 for further details.

Table 5: Coefficients on $\Delta \log GDP$ per capita in logit regressions restricted to income, education, and geographical subgroups: partial results

Subgroup	**Coef. on $\Delta \log GDP$**	**Standard error**	**N**	**χ^2-stat**
Lowest 10% of income	1.598***	(0.375)	823,644	26,796
Upper 90% of income	1.983***	(0.398)	2,367,993	32,116
Male, lowest 10% of income	2.113***	(0.532)	322,630	12,751
Male, upper 90% of income	1.652***	(0.509)	1,171,905	17,348
Female, lowest 10% of income	1.211**	(0.530)	501,014	13,528
Female, upper 90% of income	2.511***	(0.640)	1,196,088	14,063
Lower 70% of income	1.817***	(0.276)	3,050,146	67,151
Upper 30% of income	0.249	(1.838)	141,491	1,359
Male, lower 70% of income	1.974***	(0.372)	1,421,157	34,423
Male, upper 30% of income	−2.969	(2.367)	73,378	736
Female, lower 70% of income	1.679***	(0.413)	1,628,989	32,150
Female, upper 30% of income	5.182*	(2.934)	68,113	621
High school grad	1.640***	(0.417)	2,141,629	30,256
Not high school grad	1.897***	(0.362)	1,050,008	31,466
Male high school grad	1.392**	(0.563)	996,720	15,135
Male not high school	2.228***	(0.486)	497,815	16,521
Female high school grad	1.967***	(0.621)	1,144,909	14,866
Female not high school	1.572***	(0.542)	552,193	14,717
Living urban in 1980	1.633***	(0.332)	2,119,580	46,542
Living rural in 1980	2.098***	(0.482)	1,072,057	22,424

Notes: Income refers to family income measured in the CPS at the start of the NLMS panel around 1980. Asterisks denote statistical significance at the 1% (three), 5% (two) and 10% (one) level. Each row shows the estimated coefficient on $\Delta \log GDP$ per capita, its standard error, the number of observations, and the χ^2 statistic from a logit regression of the log odds of dying during a calendar year between 1980 and 1988, with a full set of covariates listed in Tables 1–2 (not shown), including a constant and a time trend, less the dummy variables specific to the group for which the regression is run. See the notes to Tables 1–2 for further details.

Table 6: Coefficients on $\Delta \log GDP$ per capita in logit regressions restricted to employment and occupational subgroups: partial results

Subgroup	**Coef. on $\Delta \log GDP$**	**Standard error**	**N**	**χ^2-stat**
In labor force, employed	2.390***	(0.582)	1,797,873	11,953
In labor force, employed, not working	0.291	(1.804)	125,295	992
In labor force, unemployed, looking for work	2.822	(2.183)	148,429	732
Not in labor force	1.689***	(0.319)	956,701	31,277
Professional/technical	−0.952	(1.549)	329,162	1,921
Managers/administrators, except farm	4.364***	(1.428)	221,934	1,686
Sales workers	3.657*	(2.039)	132,366	1,149
Clerical workers	2.591*	(1.415)	397,464	2,353
Craftmen workers	1.154	(1.285)	270,915	2,007
Operatives except transport	2.731*	(1.562)	233,618	1,359
Transport operatives	6.132***	(2.299)	76,293	627
Laborers, no farm	−1.800	(2.125)	110,401	906
Farmers and farm managers	−1.303	(2.432)	38,860	647
Farm laborers/managers	2.416	(3.678)	38,261	330
Service workers, no households	2.364*	(1.349)	289,304	2,535
Private household workers	2.067	(3.883)	27,756	320

Notes: Asterisks denote statistical significance at the 1% (three), 5% (two) and 10% (one) level. Each row shows the estimated coefficient on $\Delta \log GDP$ per capita, its standard error, the number of observations, and the χ^2 statistic from a logit regression of the log odds of dying during a calendar year between 1980 and 1988, with the full set of covariates listed in Tables 1–2 (not shown), including a constant and a time trend, less the dummy variables specific to the group for which the regression is run. Those who report being employed but not having worked during the CPS survey week can either have been on vacation, ill, experiencing child-care problems, taking care of some other family or personal obligation, on maternity or paternity leave, involved in an industrial dispute, or prevented from working by bad weather. Both current and retired workers indicate their last occupation. See the notes to Tables 1–2 for further details.

Table 7: Deaths by cause in 8 groupings, annual records in the NLMS from 1980–1988

	Cause of death	**Number**	**%**
1	Heart and hypertensive disease	16,083	38.4
2	Malignant neoplasm	10,261	24.5
3	Cerebrovascular disease	2,977	7.1
4	Infectious diseases	1,890	4.5
5	Violent deaths	2,692	6.4
6	Stomach, liver, and kidney diseases	1,237	2.9
7	Senility without psychosis	22	0.1
8	Other causes	6,651	15.9
	No cause on record	122	0.3
	All deaths	41,935	100.0
	Exposures	5,577,720	

Notes: Data are from the National Longitudinal Mortality Study (NLMS). Observations are individuals observed alive and either surviving or dying during each year between 1980 and 1988, where annual observations are pooled. Deaths by causes, categorized in ICD-9, are grouped according to the scheme suggested by Vaupel and Romo (2003) and the Berkeley Mortality Database (2006) in Japanese data. Other causes include congenital malformations and diabetes mellitus. Infectious diseases include pneumonia and bronchitis.

Table 8: Coefficients on $\Delta \log GDP$ per capita in logit regressions of deaths by cause: partial results

	Cause of death	Coef. on $\Delta \log GDP$	Standard error	N	χ^2-stat
1	Heart and hypertensive	1.030**	(0.434)	3,191,637	33,218
2	Malignant neoplasm	1.745***	(0.534)	3,191,637	13,598
3	Cerebrovascular disease	3.001***	(1.000)	3,191,637	7,137
4	Infectious diseases	2.478*	(1.333)	3,191,637	4,152
5	Violent deaths	2.761***	(1.072)	3,191,637	992
6	Stomach, liver, and kidney	3.046**	(1.547)	3,191,637	1,697
7	Senility without psychosis	17.284	(13.262)	2,271,726	137
8	Other causes	2.258***	(0.680)	3,191,637	12,020
	All deaths	1.784***	(0.273)	3,191,637	68,901

Notes: Asterisks denote statistical significance at the 1% (three), 5% (two) and 10% (one) level. Each row shows the estimated coefficient on $\Delta \log GDP$ per capita, its standard error, the number of observations, and the χ^2 statistic from a logit regression of the log odds of dying from the cause listed during a calendar year between 1980 and 1988, with the full set of covariates listed in Tables 1–2 (not shown) including a constant and a time trend. Sample size for See the notes to Tables 1–2 for further details.